Character development and the role of individual & contextual supports:

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CHARACTER DEVELOPMENT AND THE ROLE OF INDIVIDUAL & CONTEXTUAL SUPPORTS

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Abstract

This dissertation considered character development in adolescence from a relational developmental systems (RDS) perspective through the estimation of trajectories of five character attributes and the associations of these trajectories with the contextual factors of intentional self-regulation (ISR) and prosocial socialization from role models whom adolescents reported knowing personally. Character attributes considered were honesty, humility, diligence, future mindedness, and purpose. Data were taken from the Connecting Adolescents' Beliefs and Behaviors longitudinal study of character development in adolescents from the Northeastern United States. Results demonstrated that multiple trajectories can be estimated for each character attribute, supporting the RDS principles of plasticity and individual differences. Associations were also found among all character attributes considered at every time point. Contextual factors had more nuanced relationships with character attribute trajectories than was expected, with high levels of ISR associated with high start points for all character attributes and for overall character attribute patterns, but not necessarily with sustained high levels of character attributes. Prosocial socialization did not demonstrate a stable association with high levels or increasing levels of any character attribute examined. This pattern of findings suggests that additional contextual aspects should be considered as important aspects of character development. Limitations and future directions are discussed.

Keywords: adolescent development, diligence, future mindedness, honesty, humility, intentional self-regulation, other-oriented goals, prosocial goals, prosocial socialization, positive youth development, purpose, relational developmental systems, socialization

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Problem Statement

Character is the way in which individuals act so as to promote the good in their relationships with others and in their contexts by doing the right thing (Berkowitz, 2011; Lerner & Callina, 2014). Researchers and practitioners have focused on understanding aspects of character and how character can be promoted in schools (e.g., Berkowitz, 2011; Pala, 2011) so as to help adolescents develop into thriving, morally sound individuals who contribute to their communities. Callina and Lerner (2017) described character as a multi-faceted system that can promote adaptive relations between persons and their contexts toward mutually beneficial ends (i.e., thriving). However, there is limited empirical support that supports the understanding of character as a multi-faceted system.

Researchers have found that teachers and other close, caring adults, including parents, can serve as contextual resources that can be used to promote character development by modeling character themselves as well as by introducing youth to character models (e.g., Bowers et al., 2011; Narvaez & Lapsley, 2008; Oman & Thoresen, 2003). Further, character development has been linked to the development of other adolescent indicators of thriving, such as intentional self-regulation (ISR; Bowers et al., 2011; Schmid et al., 2011). However, these links have not been established when considering character as a multi-faceted system.

In this dissertation, my aim was to establish an understanding of a subset of the multi-faceted character system, operationalized as five co-acting character attributes, during part of adolescence. I considered how this subset of character attributes develops over a two year period, and how changes within this subset of the character system were associated with youth individual strengths and ecological assets. Specifically, I considered trajectories of five character attributes over a two year period and how the development of these attributes was associated with the contextual factors of ISR and prosocial socialization by role models. The attributes I considered were honesty, humility, diligence, future mindedness, and purpose. In considering associations between trajectories of these attributes and contextual factors, my aim was to contribute to the study of adolescent character development by providing empirical support for a subset of the multi-faceted character system, and for ISR and prosocial socialization as potential contextual ways in which to promote development of youth character attributes.

Relational Developmental Systems and Positive Youth Development

The study of character development in adolescence owes its existence to the shift in the field of adolescent development from a focus on youth deficits to a focus on youth strengths and plasticity in youth attributes. Until the late 1990s, adolescence had been predominantly viewed from a deficit model, which considered adolescence to be full of storm and stress (Hall, 1904). Interests in the strengths of youth and the relative plasticity of human development coalesced in the 1990s to foster new ideas about youth development from a strengths-based perspective, called Positive Youth Development (PYD; Lerner, Lerner, Bowers, & Geldhof, 2015). Rather than focusing on youth difficulties, PYD researchers considered youth as possessing strengths which, when aligned with positive contextual assets, were the critical components to promoting thriving (Lerner et al., 2015). Lerner et al. (2015) noted that focusing on youth strengths provided the framework for researchers to study positive aspects of youth development, such as William Damon's focus on youth purpose, Reed Larson's focus on motivation and engagement, and Ann Masten's focus on resilience. Lerner and Callina (2014) suggested that Relational Developmental Systems (RDS) and PYD could also be the framework for studying youth character development because the PYD framework allowed researchers to consider character as an index of thriving that can be positively influenced by contextual factors. Next, I review theoretical aspects of RDS and PYD that are important to understand as the framework for this dissertation.

The frame for PYD scholarship is based in RDS metatheoretical models (Overton, 2015). Two key facets of theories framed by RDS are the ideas that individuals change over time (i.e., plasticity) and that these changes are different between persons (i.e., interindividual; Lerner et al., 2015). RDS models emphasize that the basic process of human development involves mutually-influential relations between the developing individual and the multiple levels of his or her changing context. *Relations* between persons and contexts, rather than persons or contexts (i.e., nature or nurture), are viewed as the primary unit of analysis from an RDS perspective (Overton, 2015). These bidirectional person-context relations can be represented as individual ←→ context relations. When these developmental regulations involve individual ←→ context relations that benefit both the person and his or her context, they can be termed “adaptive” (Brandtstädter, 2010). Persons, contexts, and individual ←→ context relations are all understood to have plasticity.

RDS models would seem to task researchers with a heavy burden. The goal of research within an RDS framework is to determine how to best optimize individual ←→ context relations so as to promote thriving for all persons. However, it is impossible for researchers to focus on every component of this system at once. To optimize the ability to promote positive development, researchers must focus in on particular features of individuals and their contexts, with the goal of integrating lines of research to gain a fuller understanding of the processes of youth thriving. In this dissertation, I considered the development of specific character attributes in adolescence, looking at associations between five character attribute trajectories and the contextual factors of ISR as a youth strength and prosocial socialization by a known role model as an ecological asset. Having an RDS focus allowed me to provide recommendations on how aspects of character development could potentially be optimized through promotion of the contextual factors of ISR and prosocial socialization.

Previous Findings in Positive Youth Development

As noted above, Lerner and colleagues (2015) reported that RDS provided the framework for researchers to study positive aspects of adolescent development such as purpose, motivation, and resilience. In 2002, Lerner, Lerner, and colleagues embarked on the 4-H Study of PYD, which was the first empirical investigation of the entire RDS-derived PYD perspective (Lerner et al., 2015). The 4-H study considered the full model of PYD, including multiple individual youth strengths and ecological assets, PYD, risk behaviors, and contribution back to themselves, their families, their schools, and their societies through survey data of youth in communities throughout the United States. PYD was operationalized as an index of youth thriving consisting of five factors: Caring, Connection, Character, Competence, and Confidence (i.e., the Five Cs). The RDS framework allowed researchers for the 4-H study to recognize that there are many different components to PYD, to consider these different components in separate analyses, and to integrate the results of these analyses towards the tests of full Lerner and Lerner model of PYD. The RDS framework also allowed researchers to consider the impact of adolescent individual strengths and ecological assets more deeply while acknowledging the inseparability between individual strengths and ecological assets. Ultimately, the RDS framework permitted the study of each attribute of youth development separately while promoting the integration of the lines of research for full picture of youth development.

Central to the many findings from the 4-H Study of PYD was empirical support for the Five Cs model of PYD as a way of operationalizing adolescent thriving (e.g., Bowers et al., 2010; Phelps et al., 2009). In addition, there was support for contextual factors that could promote thriving, including individual strengths and ecological assets. ISR, considered an individual strength, was related positively to PYD and negatively to risk behaviors and depressive symptoms (Gestsdóttir & Lerner, 2007; Gestsdóttir, Lewin-Bizan, von Eye, Lerner, & Lerner, 2009). Ecological assets such as family support and family collective activity were central to goal optimization within ISR, indirectly connecting family support to the Five Cs (Bowers et al., 2011; Theokas & Lerner, 2006). Additionally, when there was a mutually adaptive fit between individual strengths and ecological assets (i.e., individual ←→ context relations), aspects of thriving were promoted. For example, Napolitano et al. (2011) found that above-median levels of goal selection and positive parenting practices (e.g., warmth and monitoring) together promoted PYD. Bowers and colleagues (2012) found that the quality of relationships with important nonparental adults was related to hopeful future expectations, which promoted thriving as measured by Confidence, Character, and Caring. Further, and most relevant to this dissertation, Bowers et al. (2012) found that higher ISR was related to positive changes in Character. Additionally, Theokas and Lerner (2006) found that important adults in the lives of youth can promote overall PYD and contribution to family, school, and society. These examples demonstrate how the RDS framework of the study allowed 4-H researchers to consider each aspect of the PYD model more deeply and then to integrate these findings to provide empirical support for the full PYD model. These findings also support my further exploration of how ISR and prosocial socialization are associated with character development by demonstrating associations between ISR and adult social support with an aspect of youth thriving.

The results of the 4-H Study of PYD provided an empirical basis for understanding many individual strengths and contextual assets that can work together to promote PYD as a whole. As noted above, some PYD researchers have investigated more deeply concepts such as youth purpose, faith and spirituality, and resilience (Lerner et al., 2015). At the same time, there has been a call for a fuller understanding of character from an RDS perspective (Lerner & Callina, 2014). Specifically, researchers are working to develop an understanding of how to define and promote character (Callina et al., 2017). In this dissertation, I built on the abovementioned findings and answered this call by looking more deeply into the Character aspect of the Five Cs as well as how ISR and prosocial socialization from known role models could contribute more specifically to the development of Character within a subset of the multi-faceted character system.

PYD, Character, and Character Development

As noted above, character is understood from an RDS perspective to be a multi-faceted construct consisting of moral emotions, cognitions, motivations, and actions (Callina & Lerner, 2017). Lerner and Callina (2014) advocated for a definition of character that includes character virtues as forming the "moral core" of the character system (p. 20). However, the understanding of the multi-faceted definition character in adolescence from an RDS perspective has been largely based on theoretical arguments rather than empirical evidence (Lerner & Callina, 2014). Efforts are currently ongoing to establish an empirical basis for understanding and promoting character development (e.g., Callina et al., 2017; Johnson, Tirrell, Callina, & Weiner, 2018). Further, researchers have advocated for the examination of character as *set* of attributes, rather than as individual attributes or pairs of attributes, so as to best understand how attributes can work together to promote prosocial behavior (e.g., Park, 2004; Peterson & Seligman, 2004). Some researchers are critical of defining character by a number of "traits," arguing that this definition of character decontextualizes the study of character (e.g., Nucci, 2017). However, Callina and Lerner (2017) argued that the study of character as a set of attributes is appropriate as long as contextual factors are adequately represented. As such, this dissertation considered the development of five character attributes, as a subset of the multi-faceted character system, as well as the contextual factors of ISR and prosocial socialization. In doing so, I contributed to a fuller understanding of the development of a subset of the multi-faceted character system within a short period in adolescence while considering potential contextual influences.

The character attributes that I focused on in this dissertation are honesty, humility, diligence, future mindedness, and purpose. These attributes have been examined individually and in subsets, but not, to my knowledge, as a set. However, existing research suggested that these attributes can function as a subset of the multi-faceted character system. For example, purpose could provide a framework toward which the other attributes can be focused (Han, 2015). This purpose-guided framework could be grounded in honesty and humility, with diligence and future mindedness focusing a person toward achieving their purposeful goals. The research reviewed below provides further evidence for the known and expected relations between these attributes and the contextual predictors of ISR and prosocial socialization.

In this dissertation, I used data from the Connecting Adolescents' Beliefs and Behaviors (CABB) study to establish an empirical understanding of the development of a subset of the multi-faceted character system, as well as associations between ISR and prosocial socialization with character attribute development. This dissertation is based in RDS principles. Based on RDS principles of plasticity and individual differences, I expected that not only would levels of character attributes change but that changes would manifest differently within subgroups of participants. I employed growth mixture modeling techniques, which allowed me to consider changes in character attributes and whether subgroups of trajectories existed for each attribute. In addition to considering the existence of multiple trajectories within the character attributes honesty, humility, diligence, future mindedness, and purpose, I considered how the contextual factors of ISR and prosocial socialization were associated with these trajectories. I expected that optimal trajectories of character attributes (e.g., high and consistent character or increasing character) would co-exist within persons and that higher levels of ISR and prosocial socialization would promote convergence of optimal trajectories. For example, I expected that if a person was in a trajectory group characterized by high and stable honesty that they would also be in trajectory groups characterized by increasing or high and stable humility, diligence, future mindedness, and purpose. Further, I expected that individuals with these patterns of character attribute development (i.e., convergence of high levels of character attributes) would have higher levels of ISR and prosocial socialization. Through these analyses, I provided empirical support for an understanding of a subset of the multi-faceted character system from an RDS perspective. Next, I review the history of the CABB study from which these data were derived.

The Connecting Adolescents' Beliefs and Behaviors study. The Connecting Adolescents' Beliefs and Behaviors (CABB) study was a mixed-method, longitudinal study that was undertaken to look further into the development of specific character attributes in youth, and aspects of individual strengths and contextual assets that promote the development of these attributes (Lerner, Johnson, et al., 2013). Youth participants in the CABB study were asked questions about their individual strengths and character attributes. In addition, youth participants were asked to name a person who they looked up to as an example of how to be a good person (i.e., *character role model*). Participants were asked questions about their role model's characteristics, the quality of their relationship with this person, and the ways in which this person promoted youth prosocial behaviors. Researchers were interested in whether ISR (Gestsdóttir & Lerner, 2008) could be a process through which ecological resources, such as close relationships with character role models, could be optimized to promote development of character attributes (Lerner, Johnson et al., 2013). Although data were collected on many character attributes, the five attributes abovementioned were the main focus of the CABB study due to their prevalence in the character literature as well as their associations with thriving (Lerner, Johnson et al., 2013).

Intentional self-regulation. ISR was considered in the CABB study as a key individual strength and the potential process by which individuals could most benefit from relationships with positive role models. ISR has been operationalized as the process by which individuals Select goals, Optimize resources towards these ends, and Compensate when access to resources is lost (SOC; e.g., Freund & Baltes, 2002; Gestsdóttir & Lerner, 2008). ISR has been shown to provide protective effects against engagement in risk behaviors, as well as to promote contribution to self, family, school, and society (i.e., contribution; Bowers et al., 2011; Gestsdóttir & Lerner, 2007), and thereby to promote youth thriving. Individual and contextual changes during adolescence make this time period key for the development of ISR (Gestsdóttir & Lerner, 2008). In this dissertation, I considered how ISR co-acts with prosocial socialization practices by a known role model to promote development of a subset of attributes within the multi-faceted character system.

Prosocial socialization. CABB study researchers considered character role models to be contextual resources who could promote youth character development through modeling and teaching prosocial behaviors in close, caring relationships with adolescents. Socialization theory, as reviewed by Bugental and Grusec (2006), provided a framework for understanding how character role models may promote character development. The basic premise of socialization theory is that adults help children to develop the competencies that enable the children to thrive within their context (Obgu, 1979). Cultural socialization theory expanded socialization theory to posit that modeling by adults is shaped by and towards goals embedded in the culture in which it occurs (Bugental & Grusec, 2006). Cultural socialization fits well with RDS because it pre-supposes that child rearing is influenced by contextual factors including settings, customs, and belief systems and that socialization aims to create the best fit between a child and their culture.

In the CABB study, researchers chose to consider socialization agents of the adolescent's choosing – persons whom the adolescent felt were influential toward their understanding of how to be a good person. By allowing adolescents to name their own role models, CABB study researchers moved towards models consistent with RDS, which emphasize the role of the person in their own development and the inevitability of bidirectional causality as well as the role of contextual influences outside of parent-child relationships, which were the original focus of socialization theory. Expanding potential socialization agents allows researchers to consider the important persons in a youth's life – including, in some cases, parents - that youth personally see as socializing them toward prosocial behaviors (i.e., *prosocial socialization*), thereby potentially promoting youth character. In this dissertation, I considered how prosocial socialization by known role models was associated with the development of a subset of the multi-faceted character system.

The current study

In this dissertation, I considered the development of part of the multi-faceted construct of character through examination of the five key character attributes noted above. I considered trajectories of each of these attributes, using growth mixture modeling techniques to explore subgroups of trajectories for each character attribute. I compared these trajectories between attributes to learn about the development of five key attributes within the character system over a period within adolescence. Finally, I considered how the contextual factors ISR and prosocial socialization practices, were associated with these trajectories and convergence of optimal trajectories.

I hypothesized that trajectories of each character attribute considered would be significantly and positively associated with one another, such that participants classified in a trajectory characterized by moderate and increasing honesty, for example, would be more likely to also be classified in a trajectory characterized by increasing or high and stable humility. Further, I hypothesized that higher levels of ISR and prosocial socialization practices would be identified among participants showing optimal trajectories of each character attribute (i.e., high and stable or moderate and increasing). Finally, I hypothesized that higher levels of ISR and prosocial socialization would predict convergence of optimal trajectories, providing evidence that ISR and prosocial socialization can promote confluence of high levels of character attributes. Overall, in this dissertation, I aimed to contribute to the developmental literature, and specifically to the emerging research in character development from an RDS perspective, by providing a deeper empirical understanding of the development of five key character attributes within the multi-faceted character system during a period in adolescence, as well as how changes in character attributes were associated with the contextual factors of ISR and prosocial socialization by known role models.

Literature Review

Relational Developmental Systems

The present study is framed by RDS metatheory, which is an outgrowth of the anti-reductionistic movement in developmental science (Lerner, 2018). RDS is a middle-range metatheory within the process relational worldview through which lifespan development can be considered (Overton, 2015; see Figure 1 [J. Lerner, personal communication, February 22, 2017]). Working within the RDS metatheory allows researchers to consider all of the different levels of organization in which lifespan development exists and how these levels can co-act to promote optimal development (Lerner, 2018; Overton, 2015). I review one of the bases of RDS metatheory to provide context for the RDS perspective. Specifically, I discuss the concept of probabilistic epigenesis, developed by Gottlieb and reviewed by Lerner (2018), which provides the basis for RDS researchers' understanding of personal attributes as always susceptible to change (i.e., plasticity). Probabilistic epigenesis is important to my dissertation as it provides the rationale for examining trajectories of character attributes.

Probabilistic epigenesis. One of the major tenets of RDS, plasticity, is based in Gottlieb's concept of probabilistic epigenesis. Lerner (2018) provided a review of Gottlieb's concept of probabilistic epigenesis and its influences on RDS metatheory. Lerner (2018) reported that Gottlieb posited that the cause of development is the relations between components rather than components themselves. The four components of Gottlieb's theory as reviewed by Lerner (2018) were 1) Changing organism-context coactions; 2) A focus on context; 3) The idea that individuals could differ from one another; and 4) The concept of plasticity (i.e., ability to change, malleability) throughout the life-span. According to Lerner (2018), Gottlieb's view challenged the ideas of innateness and of genetic determinism and promoted the concept that mutually influential person-context relations could influence ontogenetic, or *organismic*, development, which in turn can, over time, influence phylogenetic, or *evolutionary*, development. The idea that phylogenetic development could be influenced by ontogenetic development was in contrast to popular notions that ontogeny recapitulates phylogeny, and instead promoted the idea that individual experiences could, when appropriate, be aggregated to more fully understand the human evolutionary experience.

Probabilistic epigenesis stood in contrast to the popular theory that genes are not susceptible to contextual influence. Lerner (2018) wrote that Gottlieb asserted that all cells are susceptible to environmental influence and therefore subject to change, and that there is nothing "fixed" about development. Gottlieb used an example of hormone secretions based on a mother's experiences affecting fetus development to provide evidence that, even in the womb, an organism is thoroughly intertwined with its environment. This way of understanding susceptibility to environmental influences is central to PYD research. It provided a contrast to the deficit model of adolescent development, which relied personality traits as the basis of behavior and did not allow for plasticity or positive growth in adolescence. Probabilistic epigenesis is central to this dissertation because working from this theory means that there are opportunities for continued growth during this, and any, period of ontogenetic development that can be more fully explored and understood so as to optimize human development. Specifically, probabilistic epigenesis provides the rationale for exploring the development of, and influences on, character attributes, rather than considering character attributes to be static "traits" of persons. In fact, from an RDS perspective, there is no attribute that is not vulnerable to change, in any direction (Overton, 2015).

Developmental contextualism. Partially an outgrowth of Gottlieb's probabilistic epigenesis, developmental contextualism was the first topic-specific theory on human development from the RDS perspective (Lerner, 2018). Developmental contextualism focused more narrowly on parent-child relations and promoted that, rather than children only being shaped by parenting in a uni-directional process, children and parents shape one another's development in a bi-directional manner (Lerner, 2018). For example, a child with a particular temperament evokes a particular reaction from parents, which can shape parenting behaviors and thereby shape the development of that child. In this way, individuals are part of the system that shapes their own development. Further, mutually adaptive relations between person and context can promote adaptive developmental trajectories. Developmental contextualism was established in an attempt to translate the views of Gottlieb and other prominent researchers (e.g., Schnierla) into an ontogenetic theory of development which valued plasticity and person ←→ context relations (Lerner, 2018). Developmental contextualism provided the theoretical basis for PYD and advanced the field of developmental psychology toward considering the mutually influential relationships between youth and adults, a focus of this dissertation, thus allowing researchers to consider how individuals could maximize the benefits of social relationships by using their own strengths to optimize what they could gain from those relationships. In this dissertation, I considered ISR and prosocial socialization together with the assumption that higher levels of ISR can optimize benefits gained from prosocial socialization from known role models, thereby maximizing the benefits of each.

The Lerner and Lerner Model of PYD. Developmental contextualism was a precursor to the Lerner and Lerner model of PYD (e.g., Lerner et al., 2015), which is a theory and framework for understanding RDS within the first three decades of a person's lifespan. PYD grew out of developmental contextualism but aimed to consider settings outside of the parent-child relationship (Lerner, 2018). PYD researchers seek to define and understand promotion of optimal developmental trajectories in adolescence toward thriving for all persons. As with all RDS-based theorists, PYD researchers also seek to work against the deficit-based and reductionistic models of adolescence (e.g., Hall, 1904) that were prevalent for much of the early research on adolescence. As per the influence of Gottlieb and developmental contextualism, PYD researchers promote adolescence as a time period of extensive changes and plasticity, and therefore full of opportunity for positive growth. The 4-H Study of PYD provided the first empirical evidence of the full PYD model, substantiating the theoretical argument that bidirectional relations between individual youth strengths and ecological assets can co-act to promote PYD, which can be associated with contributions back to family, school, and society as well as decreases in problem behaviors (e.g., Lerner et al., 2011).

Based on the results of the 4-H study of PYD, the Lerner and Lerner PYD model considers PYD to consist of the *Five Cs*. These include Caring, Character, Competence, Connection, and Confidence (Lerner et al., 2011). The Five Cs have been associated with individual strengths, such as aspects of intentional self-regulation (e.g., Gestsdóttir et al., 2009) as well as combinations of individual strengths and ecological assets, such as goal selection and positive parenting practices (e.g., Napolitano et al., 2011). Napolitano et al. (2011) also found that adolescents with low levels of selection within ISR, and who reported lower level of close relationships with their parents, evidenced thriving. However, other researchers have found that family collective activity (i.e., the number of nights a family had dinner together) was the best predictor of positive developmental trajectories in regard to goal optimization within ISR, providing evidence for differences in associations between family collective activity and youth outcomes (e.g., Bowers et al., 2011). Theokas and Lerner (2006) found that relationships with caring, committed adults were key to youth thriving. Specifically, family collective activity predicted PYD, contribution, depression, and risk behaviors in the expected directions (Theokas & Lerner, 2006). Additionally, family and school resources predicted PYD and depression in the expected direction, and neighborhood human resources positively predicted PYD and contribution (Theokas & Lerner, 2006). These findings point to the importance of considering contextual influences on youth thriving, as well as the fact that not all youth will be affected by contextual resources in the same way.

Lerner and colleagues (2015) named positive and sustained youth-adult relationships as a central component of effective PYD programs, along with opportunities to develop life skills and opportunities for youth leadership. Although positive youth-adult relationships have largely been associated with youth thriving, Napolitano et al. (2011) provided evidence that close relationships with adults may not always be necessary for youth thriving in regard to goal optimization. Further, there has been limited exploration of adult support in regard to development of youth character specifically. These associations with thriving and previously established mixed results are central to why I studied the associations of ISR and prosocial socialization with character development in this dissertation.

Developmental contextualism (Lerner, 2018) is a framework for understanding youth-adult relationships that is also central to my dissertation. Developmental contextualism researchers considered how youth can work to optimize the benefits they gain from their individual strengths and ecological assets, and thereby positively influence their own development. RDS and PYD researchers provided an improvement upon developmental contextualism by allowing researchers to consider influential persons beyond parents. Considering influential persons beyond parents is important for this dissertation because I considered how relationships between youth and their named role models could optimize the development of their character. Although these named role models are sometimes parents, they are sometimes other persons such as teachers or coaches. The PYD model allowed me to consider these youth-adult relationships outside of parenting and how such relationships can work in conjunction with youth strengths to promote youth thriving.

Character development research. Whereas the results of the 4-H Study of PYD provided empirical support for the measurement, growth, and contextual supports for PYD as a whole, researchers have also sought to look more deeply into the development of other aspects of youth thriving. Lerner and colleagues (2015) noted that there have been researchers looking more deeply into concepts such as youth purpose, faith and spirituality, and resilience. More recently, there has been a call for an understanding of character development from a PYD perspective (Lerner & Callina, 2014). As advised by Overton (2015), character researchers grounded in RDS seek to define character, understand developmental trajectories of character, and understand what contextual influences may support character development (Callina et al., 2017). In this dissertation, I provide empirical support for an RDS-based understanding of changes in subset of character attributes within a two year period in adolescence. I consider changes in character attributes and associations with contextual factors by estimating character attribute trajectories, which illustrate the plasticity of each character attribute, as well as by considering how ISR as an individual strength and prosocial socialization as an ecological asset are associated with each trajectory and patterns of trajectories. Additionally, I consider how levels of each character attribute are associated with one another based on trajectory estimates at each time point.

An example of current research in character development is the Connecting Adolescents' Beliefs and Behaviors study (Lerner, Johnson et al., 2013). The CABB study was a three-year mixed-method study in which data were collected from youth, parents, and school staff members in the New England area. CABB study researchers sought to consider the development of character attributes in adolescence and if and how these attributes could be promoted by other individual strengths and by ecological assets, such as relationships with caring adults. Youth participants were asked about many topics including their individual strengths, character attributes, and relationships with caring adults that were good models of character (i.e., *character role models*). Youth participants were also asked about their character role model's characteristics, the quality of their relationship with this person, and the ways in which this person modeled prosocial behaviors (i.e., *prosocial socialization*;

Johnson et al., 2016). CABB researchers were specifically interested in whether ISR (Gestsdóttir & Lerner, 2008) could be the process through which contextual resources, such as close, positive relationships with character role models, could be optimized to promote development of character attributes (Lerner, Johnson et al., 2013). In this dissertation, I used data collected in the CABB study to consider character development in adolescence through examination of a subset of character attributes, and how the development of these attributes was associated with youth ISR and prosocial socialization from known character role models. Although the CABB study considered many character attributes, the five attributes emphasized were honesty, humility, diligence, future mindedness, and purpose. These character attributes were the focus of the CABB study due to their prevalence in the character literature as well as their associations with thriving (Lerner, Johnson et al., 2013).

Character and Relational Developmental Systems

Current RDS scholars assert that character is a multi-faceted construct that exists within the self-system (Callina & Lerner, 2017; Nucci, 2017). Psychologists have long been interested in understanding specific aspects of morality including moral behaviors (Bandura & Walters, 1963; Freud, 1949; McCandless, 1970), as well as moral development and moral reasoning (Kohlberg, 1958, 1963; Michel, Ebbesen, & Zeiss, 1972; Piaget, 1965). Callina and Lerner (2017) advocated for a multi-faceted definition of character that includes moral cognition, moral agency, moral performance, and contribution as parts of the character system. Character attributes were described by Callina and Lerner (2017) as a part of the "moral core" (p. 20) that makes up the character system. Nucci (2017) argued that specific attributes should not be considered in the study of character from an RDS perspective because past researchers have sought to reify a set of universal attributes toward which to strive, thereby making the study of character attributes acontextual and counter to the RDS perspective. However, Callina and Lerner (2017) argued that examining attributes as a part of character development can support an understanding of the multi-faceted character system. Further, Callina and Lerner (2017) argued that any study of character attributes should be conducted *within* a context, so as to understand the best attributes to employ in different situations. For example, they wrote that "good character for a 14-year-old high school student dealing with cyberbullying…will look different than what one would expect from a 28-year-old military officer seeking to promote discipline…within her unit" (p. 20). Thus, they support studying character attributes as a part of the multi-faceted character system, as long as contextual factors are considered.

In this dissertation, I used Callina and Lerner's (2017) perspective to consider the development of a subset of character attributes and how contextual factors may be associated with the development of these attributes. This set of character attributes includes aspects of character that are focused on moral tendencies, such as honesty and humility, as well as aspects that are more associated with carrying out of potentially moral actions, such as diligence, future mindedness, and purpose. These were the five key attributes examined as part of the CABB study due to their individual associations with positive youth outcomes as well as their prevalence in the character attribute and character education literature (Lerner, Johnson et al., 2013). Within the CABB study, ISR and prosocial socialization were key contextual factors that could predict changes in character attributes. For example, a person experiencing prosocial socialization from a role model may have higher levels of purpose toward prosocial aims than a person who is not receiving such socialization. Thus, I considered relations between levels of character attributes as well as if and how ISR and prosocial socialization from a known role model are associated with character attribute trajectories. Changes in character attributes were estimated using growth mixture modeling, which allowed me to consider subgroups of trajectories within each attribute. Growth mixture modeling is consistent with the RDS principles of plasticity and individual differences, which assume that all attributes are subject to change and that these changes may vary across persons.

After estimating these trajectories and selecting a model for each character attribute, model estimates for character attributes were computed for each time point. For example, the intercept estimate for honesty within a class was considered the start point estimate for honesty for all individual in that class. The middle point estimate was calculated by adding the slope estimate for this class to the start point, and the end point estimate was calculated by adding the slope estimate for this class to the middle point. These estimates were then correlated to consider associations between character attributes. Examining associations between these estimates allowed me to consider how each attribute was associated with the development of other attributes within subgroups of persons. Finally, trajectories and patterns of trajectories were regressed on ISR and prosocial socialization to consider associations between character attribute trajectories and contextual factors.

This investigation was important to the field of character development because it considered how a subset of character attributes are associated within the multi-faceted character system. As noted above, the attributes I considered are honesty, humility, diligence, future mindedness, and purpose, five central character attributes considered in the CABB study. Next, I review the literature on each of these five attributes, focusing on the theoretical and empirical literature on each one as well as how they may fit together in a subsystem.

Honesty. Honesty is generally considered to be an important aspect of what makes up a good person. Interestingly, in the developmental literature on honesty, research is more focused around honesty operationalized as the absence of lying (e.g., Bussey, 1992; Evans & Lee, 2013; Hartshorne & May, 1928). In fact, situational measures of honesty in studies such as Mussen, Harris, Rutherford, and Keasey (1970) were actually situational measures of not lying, rather than engaging in prosocial pursuits involving honesty. The HEXACO model of personality advanced research on honesty and humility as prosocial behaviors, but it considered honesty and humility to be a single trait not amenable to contextual influences (Ashton & Lee, 2007). The HEXACO model represented the emergence of honesty-humility as a personality trait, focused on the prosocial aspects of honesty and humility but treating them as one inseparable and immutable trait. Allgaier, Zettler, Wagner, Püttman and Trautwein (2015) contributed to prosocial studies of honesty by considering the relation between self-reported honesty-humility based in the HEXACO model, with hypothetical self-reported prosocial and antisocial behaviors on presented vignettes. The researchers found that individuals reporting themselves as higher in honesty-humility engaged in more prosocial behaviors (Allgaier et al., 2015). However, Allgaier at el. (2015) treated honesty-humility as a personality trait, changes in this attribute were not considered. Further, the HEXACO model defines honesty-humility as the tendency to not take advantage of others (Ceschi, Sartori, Dickert, & Costantini, 2016), and in this way the research on honesty-humility from the HEXACO framework, although presented as prosocial, can be considered similar to the research on lying.

In 2004, Peterson and Seligman sought to fill what they perceived as a gap in character virtue research by creating an inventory of character virtues that aimed to be the

DSM for positive characteristics. They referred to honesty and other identified character strengths as traits, which are traditionally not considered malleable or contextually-based. However, Peterson and Seligman (2004) clarified that they considered these traits to be generally stable but also capable of change based on contextual influences. Peterson and Seligman (2004) considered some strengths to be more static than others. Attributes reviewed by Peterson and Seligman (2004) that were included in this dissertation are all considered to be *traitlike* or stable. In contrast to Peterson and Seligman, this dissertation considered all character attributes to have a potential for change, per the RDS principle of plasticity. However, their research is still considered in this dissertation given the importance of their contribution to literature on character development.

Peterson and Seligman (2004) described honesty as a core character attribute that consists of truthfulness as well as authenticity. Authenticity within honesty was described as accurately describing oneself and consistency between one's principles and one's behaviors (Peterson & Seligman, 2004). Through their inclusion of honesty as a character strength, Peterson and Seligman promoted the shift toward the study of honesty as a prosocial attribute, rather than lack of lying as representative of honesty. Further, they promoted the idea that honesty was vulnerable to change based on contextual influences, but believed that it was generally stable. In this dissertation, honesty was considered a character attribute that is central to other-oriented, or *purposeful*, goals and is influenced by context. Specifically, as with all character attributes, I considered changes in honesty over time and associations between these changes and contextual influences.

In this dissertation, I considered how honesty as a character attribute could exist within a subset of the character system. As noted above, the subsystem considered included honesty, humility, diligence, future mindedness, and purpose. I incorporated honesty into this character subsystem under the theoretical assumption that honesty could provide the moral foundation that aligned other character attributes in the subsystem toward character-related behaviors. There may be situations when lying is an easier way to move toward one's goals, such as when lying about the outcome of a game is associated with prizes (e.g., Hartshorne & May, 1928). If one acts honestly in this scenario, they are less likely to get a prize. Acting honestly may be easier if one has higher levels of other character attributes, such as an overarching prosocial purpose toward which they are working, as well as the diligence and future mindedness to promote their efforts toward this prosocial purpose. Thus, an honest person could employ other character attributes, such as thinking about future and other-oriented goals, to refrain from lying behaviors. Further, honesty can work with attributes like humility to allow individuals to be honest with themselves about their abilities and standing, thereby promoting being realistic and authentic in goal pursuit as well as committing to pursuits in a moral way. Honesty has been associated with several aspects of life fulfillment, including personal well-being, persistence and self-direction, developing personal relationships, and contributing to a better country (Castro Solano & Consentino, 2016). Associations between honesty and thriving provide a foundation for examining the development of honesty in conjunction with the development of other character strengths theoretically related to thriving.

I included honesty as part of my subset of character attributes to understand more thoroughly how honesty develops from a strengths-based perspective. I aimed to build on the efforts of Peterson and Seligman (2004), who identified honesty as a strength, and to work in contrast to past studies which have considered the development of lying rather than viewing honesty from a prosocial lens (e.g., Hartshorne & May, 1928) as well as in contrast to Peterson and Seligman's (2004) conception of honesty as traitlike. Further, including honesty as part of the subset of character attributes examined allowed me to consider how trajectories of honesty were associated with optimal trajectories of other positive character attributes as well as how the development of honesty was affected by the contextual factors of ISR and prosocial socialization.

Humility. Humility includes the abilities to admit to mistakes, to be open to other perspectives, and to be grateful (Davis, Worthington, & Hook, 2010). Gratitude as an aspect of humility is typically explored separately, and it was included as a separate character attribute by Peterson and Seligman (2004). As with honesty, humility involves accurate self-descriptions. However, whereas accurate self-descriptions within honesty consist of being sincere and consistent between one's beliefs and behaviors, accurate self-descriptions within humility are more focused on the ability to acknowledge the limits of one's abilities and, therefore, to humbly learn from others. Also similar to honesty, humility is also considered by Peterson and Seligman (2004) to be a generally stable character strength. Peterson and Seligman (2004) wrote that humility may help in self-regulation toward goals because humility allows people to be honest about their current state and what goals are realistic for them.

Davis et al. (2010) described humility as consisting of four components: emotional regulation, accurate self-descriptions, an other-oriented focus, and being positive toward others in relationships. This definition of humility demonstrates the centrality of relationships with others in defining humility. Indeed, central to humbly identifying one’s weaknesses is working with others to overcome them by having individuals combine their personal strengths in achieving team goals. The centrality of relationships in this definition of humility puts humility in line with diligence in that having both requires open-mindedness and flexibility to understand and work with others in goal setting and achievement.

Further evidence for the connection between humility and other character attributes comes from Bronk (2008) in her interviews of adolescent *purpose exemplars*. Purpose exemplars were highly purposeful youth who were identified as having other-oriented life goals and working toward, or having plans to work toward, these goals (Bronk, 2008). Bronk (2008) found that aspects of humility were reported by all of the purpose exemplars interviewed, even though she did not specifically ask them about humility. Purpose exemplars appreciated the value and positive influences of others around them in working toward their other-oriented goals. This example demonstrates the connections between humility, diligence, and purpose in Bronk's (2008) sample.

Fowers and Davidov (2006) focused on the importance of openness, an aspect of humility, in promoting multicultural ends. The authors posited that individuals can only work toward multicultural ends only if they are open to learning from those who are culturally different from them. Further, they noted that in order to be open, individuals must learn from those who can model openness to others. Fowers and Davidov's (2006) reasoning is in line with this dissertation in that they posited the importance of openness, an aspect of humility, in working toward prosocial ends, as well as the importance of prosocial socialization in promoting this openness. In this dissertation, humility is operationalized as openness due to the way humility was measured in the CABB study.

Previous research provided evidence that humility, and specifically the openness to learning and personal change central to humility, is key to having positive relationships with others and developing and working toward other-oriented goals persistently, with the ability to adapt based on modeling and socialization. The centrality of relationships with others, the connection to a moral, honest, self-concept, and the focus on working to recognize ones' limits are all reasons that humility was an important character attribute to consider in this dissertation. In this dissertation, by considering trajectories of both humility and honesty, along with trajectories of other character attributes, I sought to demonstrate how humility and honesty are associated and develop with more goals-focused aspects of character to support the character system.

Diligence. Diligence is tied to self-regulatory processes (Brandtstädter, 2010; Brandtstädter & Renner, 1990) and is an attribute which promotes action toward goal attainment (Brandtstädter & Renner, 1990). Further, diligence can help individuals to recognize when goal attainment requires more resources than a person can put forth, and thereby help individuals shift to more realistic goals (Brandtstädter, 2010). Goal achievement requires flexibility to adapt appropriately to limitations in a person's context. As noted above, honesty and humility are also central to the recognition of appropriate limitations. Diligence is an appropriate attribute to consider as an aspect of character within the RDS framework because its goal-directed nature is clearly tied to embracing the plasticity of development. Further, with its clear ties to behavior, diligence is a key attribute that can promote an individual working toward prosocial goals.

Peterson and Seligman (2004) considered diligence to be a character strength that is generally stable but noted that social support may be beneficial for diligence to be maintained. They use the term persistence instead of diligence. In the context of the CABB study, diligence is operationalized as grit, or the process of actively persevering toward a goal, even in the presence of resistance (Duckworth & Quinn, 2009). Specifically, diligence is operationalized through two items from the perseverance of effort subscale on the short grit scale (Duckworth & Quinn, 2009) and one researcher-developed item. All items involved sustaining effort on goals.

Diligence as a character attribute is similar to the predictor ISR. Theoretically, both involve goal setting and attainment. In the context of the CABB study, diligence was operationalized as the perseverance of effort on goals through portions of the short grit scale (Duckworth & Quinn, 2009). In contrast, ISR is operationalized through a version of the Selection, Optimization, and Compensation scale (Gestsdóttir et al., 2009), which focuses on goal selection, resource optimization, and compensation when resources are lost. Certain aspects of self-regulation (e.g., cognitive and effort regulation) have been theoretically and empirically associated with the perseverance of effort scale within grit (e.g., Muenks, Wigfield, Yang, & O'Neal, 2017). Muenks and colleagues (2017) noted that grit involves perseverance toward long-term goals, but that perseverance *and* long-term goals are not always captured by the items used to measure grit. This is true for the items included in the CABB study, which emphasize just the perseverance of effort within grit. In contrast, ISR items consider perseverance, but also goal selection and self-monitoring toward goal achievement. Therefore, although diligence and ISR are expected to be related, they do not fully overlap.

As reviewed above, in Bronk (2008), ties between humility, grit, and purpose were explored. Hill, Burrow, and Bronk (2016) further considered relations between grit and purpose. In a longitudinal study with college undergraduates, the researchers found that purpose, defined as commitment to a life goal, predicted grit. They hypothesized that purpose commitment may have encouraged grit development because grit was the way in which goals could be achieved. Further, it may be easier to be *gritty* if one has an explicit goal toward which they are working. Von Culin, Tsukayama, and Duckworth (2014) also considered associations between grit and long-term goals, which are aligned with the operationalization of purpose in this dissertation. Von Culin et al. (2014) found that individuals higher in grit were interested in other-oriented goals. Previously identified associations between grit and other attributes considered in this dissertation provided a basis for exploring trajectories of diligence in this dissertation.

Future mindedness. Future mindedness, also called future orientation, is the concept of being focused on future goals and intentions (Hoyle & Sherrill, 2006; Malmberg, Ehrman, & Lithén, 2005; Steinberg et al., 2009). Having a future orientation can promote self-regulation toward goals by helping an individual to visualize possible end points (Brandtstädter, 2010; Hoyle & Sherrill, 2006). In addition to thinking about the future generally, Steinberg et al., (2009) found that having a future orientation could help individuals anticipate consequences, supporting planning ahead to avoid or work toward these ends. Beyond having a direct association with planning, researchers have found that having a future orientation can be related to identity development (Malmberg et al., 2005) and that future orientation tends to grow with age (Steinberg et al., 2009). Within Peterson and Seligman's model (2004), future mindedness is considered under the character strength of hope. As with abovementioned character attributes, Peterson and Seligman (2004) see future mindedness as generally stable.

Peterson and Seligman (2004) and other researchers have associated future mindedness with other character attributes to be considered in this dissertation. Specifically, Peterson and Seligman (2004) noted that a future orientation is necessary to develop and achieve goals. This understanding of future mindedness aligns future mindedness with goal setting, the operationalization of purpose within the CABB study. Stoddard and Pierce (2015) directly considered associations between positive future expectations, operationalized as expecting positive future outcomes, and purpose, operationalized as having a purpose in one's life, and found that "higher purpose was associated with higher future expectations" (p. 337).

Based on these findings, future expectations that are aligned with other-oriented, purposeful goals could promote movement toward these goals by providing an end point toward which to work. In addition, having a strong future orientation could promote development of other-oriented goals and diligence in movement toward these goals (Nurmi, 1992; Peterson & Seligman, 2004; Snyder, 1995, 2002). In a study focused on citizenship behaviors within organizations, Strobel and colleagues (2013) found that having a future focus influenced self-regulation toward being a good citizen within an organization, an endpoint that is an example of other-oriented, purposeful behavior. Although Strobel and colleagues (2013) focused on self-regulation as an outcome of future focus, the authors defined self-regulation as regulatory focus (e.g., promotion or prevention focus) toward future goals. A promotion focus involved working toward goals proactively whereas a prevention focus involved avoiding losses in working toward goals. This operationalization of self-regulation, specifically the promotion focus, aligned more closely with my operationalization of diligence, which involved perseverance of effort, than with my operationalization of self-regulation, which involved goal setting as well as self-monitoring.

These studies provide empirical evidence for the alignment of different character attributes which were explored in this dissertation.

The CABB study adapted three items of the Steinberg et al. (2009) future orientation scale to measure future mindedness. The subscales reflected in the future orientation scale included anticipation of future consequences, planning ahead, and time perspective (Steinberg et al., 2009). Future mindedness as operationalized within the CABB study includes items adapted from the anticipation of future consequences subscale. Higher levels of anticipation of future consequences were found by Steinberg and colleagues (2009) to be associated with preferences for "larger, delayed" rewards (p. 39). This association between anticipation of future consequences and delayed rewards provided a basis for considering that higher levels of future mindedness in this dissertation were associated with preference for other-oriented, longer-term goals. Higher levels of multiple character attributes, such as future mindedness and other-oriented purpose, may be associated with other-oriented goal achievement and positive consequences for communities. Thus, future mindedness was an important attribute to study within this dissertation because future mindedness could help individuals envision a possible end point, potentially involving contribution to one's community. Envisioning this endpoint using future mindedness and other-oriented purpose could enable individuals to work toward it (Hoyle & Sherrill, 2006), using character attributes such as diligence to achieve these ends.

Purpose. Purpose is a construct that has been widely investigated by PYD researchers (e.g., Bronk, 2008; Bronk, 2014; Damon, 2008; Damon, Menon, & Bronk, 2003; Liang, Lund et al., 2017; Liang, White, et al., 2017). Damon et al. (2003) defined purpose as "a stable and generalized intention to accomplish something that is at once meaningful to the self and of consequence to the world beyond the self" (p. 121). This definition was meant to encompass the long-term prosocial intentions, motivation toward other-oriented goals, and commitment and planning toward prosocial goals (Damon, 2008). This definition of purpose has largely framed PYD research into purpose since 2003.

Although purpose shares the goal-directedness of future mindedness and diligence, it is unique as a character attribute because purpose incorporates personal values and other-oriented goals to serve as a framework that could guide an individual toward prosocial ends. Purpose commitment plays a central role in identity development and well-being and directs individuals toward goals that benefit others (Bronk, 2012; Burrow & Hill, 2011; Burrow, O'Dell, & Hill, 2010). In interviews with adolescent purpose exemplars, Bronk (2012) found that purpose exemplars were able to appreciate the work they had completed while also acknowledging and persisting with the work left to do. These adolescents had an overarching purpose to their work which promoted their ability to have a future focus and diligence in moving toward their goals, directly exemplifying several character attributes including purpose, future mindedness, diligence, and humility. Bronk's (2012) findings provided evidence that having a purpose can provide overarching support for future mindedness and diligence in more difficult times, as hypothesized by Han (2015).

Youth purpose has also been considered longitudinally and within contexts. Malin, Reilly, Quinn, and Moran (2014) found that the development of purpose is strongly influenced by contexts and opportunities. Specifically, they found that young adolescents who wanted to help others often presented as empathetic toward others' needs (e.g., wanting to help persons experiencing homelessness) but not as actively engaging in prosocial goals (Malin et al., 2014). Middle-age adolescents had a stronger desire to engage with and have an impact on their context, thus developing values oriented toward helping others. In later adolescence, goals were developed to fit with the values structured in middle adolescence. Strong, positive relationships with caring adults helped to form these goals and to support prosocial behaviors, especially later in adolescence. Youth in college experienced greater opportunities to consider the purpose of their lives and to develop goals. In contrast, when youth started in their careers after college, many became more focused on self-interest and financial stability, demonstrating that purpose does not necessarily continue to increase (Malin et al., 2014). Quinn (2016) also considered purpose development in early adolescence and found that the other-oriented dimension to purpose was rare for adolescents and early adults, although there was evidence that it was more common than chance in college students and less common than chance in middle school students, suggesting that purpose could grow with age. These studies suggest that commitment to other-oriented, purposeful goals is less common in early adolescence, and develops more fully with development of values and social support. However, other commitments and changes in values may impact the ability for sustained purposeful actions.

In the CABB study, purpose was operationalized as identified life goals, or the long-term intentions portion of purpose as defined by Damon et al. (2003). Researchers have studied this *life goals* aspect of purpose previously and its connection with the other character attributes in this dissertation. Massey and colleagues (2008) noted that having a purpose overarching one's goals and a future orientation to identify and work toward these goals can promote goal pursuit. In regard to positive outcomes associated with other-oriented goals, in Emmons's (2003) review of literature on personal goals, life meaning, and virtue, working toward generative, other-oriented, goals was associated with life satisfaction and positive affect. Further, Yeager and Bundick (2009) found that having purposeful work goals could help people determine who they want to be, and thereby motivate them to become that person. Thus, purpose as operationalized by prosocial goals has been associated with other character attributes, such as future mindedness and diligence, as well as positive outcomes, such as engagement toward these other-oriented goals and life satisfaction.

As noted above, diligence and future mindedness also involve life goals. Life goals within purpose as defined in the CABB study consist of having specific prosocial goals in mind. Diligence and future mindedness can be employed to promote movement toward these prosocial goals. However, goals within diligence and future mindedness are not necessarily focused on others (Malin, Liauw, & Damon, 2017). Thus, it is important to consider diligence and future mindedness in conjunction with other attributes that have a prosocial focus, such as purpose, in order to include them as part of this character subsystem. Han (2015) hypothesized that "purpose provides other virtues with the proper direction where they should aim, and when and where they should be put into practice" (p. 297). Similarly, Linver and Urban (2018) wrote that purpose creates a foundation for thriving by helping individuals develop long-term goals that could set the stage for short-term goals. Thus, purpose was important to study within this dissertation as identifying important other-oriented goals that could promote the advancement of other character attributes in an attempt to reach such goals.

Summary. In this dissertation, I considered developmental trajectories of the five abovementioned character attributes, and whether there are comparable developmental trajectories for each attribute within persons. Understanding how each attribute develops within a person in relation to the development of other attributes enabled me to see different ways in which this subset of the multi-faceted character system manifests during a period of adolescence. Considering how ISR and prosocial socialization are associated with these trajectories and with potential convergence of these trajectories further allowed me to understand whether there are ways in which contextual factors could be employed to promote movement toward or maintenance within optimal character development trajectories.

The character attributes included in this dissertation involve different strengths within character development, from strengthening one's moral core to promoting engagement in goals that could be toward moral ends. Within each the summary of each character attribute, I have provided evidence as to how they may work in conjunction within youth development. Briefly, honesty and humility may promote development of purposeful, other-oriented goals and actions toward them (e.g., Castro Solano & Consentino, 2016; Fowers & Davidov, 2006). Further, having other-oriented goals can induce future orientation and grit in pursuit of such goals (e.g., Bronk 2008; Hill et al., 2016; Nurmi, 1992; Peterson & Seligman, 2004; Snyder, 1995, 2002; Stoddard & Pierce, 2015; Strobel et al., 2013; Von Culin et al., 2014). Finally, purpose can act as the overarching framework for character attribute development by providing an endpoint and motivation for the development of the other attributes (Han, 2015; Linver & Urban, 2018). In addition to considering trajectories of these attributes and associations between them, I considered how optimal trajectories of all five of these character attributes may be predicted by ISR as well as prosocial socialization practices. Next, I review how these contextual factors may provide an important context for the development of these character attributes.

Intentional self-regulation

It follows from RDS that youth strengths and aspects of youth-adult relationships can be mutually influential towards promoting optimal character attribute trajectories. Specifically, adults could maximize their positive impact on youth by working with young people's internal strengths, and youth could use their internal strengths to optimize the resources they receive from adults. In this dissertation, I was interested in considering the role of ISR as an individual strength to promote character development.

ISR is an internal strength that has been specifically associated with youth thriving (Gestsdóttir & Lerner, 2007; Gestsdóttir et al., 2009). ISR involves regulation between a person and their context so as to promote achievement of goals and/or prevent a loss of resources. In a review of ISR by Gestsdóttir and Lerner (2008), the researchers described the distinction between intentional and organismic self-regulation. They noted that, prior to adolescence, self-regulation is typically focused on self-control. Self-control is central to organismic self-regulation because it helps regulate human processes like breathing. In contrast, ISR involves engaging in effortful control toward long-term goals. ISR necessarily involves self-monitoring to assess the gaps between a person's present and future states and to help individuals make appropriate choices so as to narrow the gap between the present self and the ideal self. ISR is identified as beginning to develop in early adolescence and is operationalized as selecting goals, optimizing resources, and compensating for lost resources in pursuit of goals (Gestsdóttir & Lerner, 2008).

Researchers have demonstrated that youth who have high levels of ISR skills can best take advantages of resources in their context (e.g., Mueller et al., 2011; Urban, Lewin-Bizan, & Lerner, 2010) because ISR abilities allow them to have more control over goal setting and pursuit. Therefore, ISR skills may be tools that youth can use to best gain resources from interactions with committed and caring adults which can promote character development. In this dissertation, I considered how ISR may help adolescents to further benefit from prosocial socialization practices in promoting development of character attributes by considering how both contextual factors are associated with character attribute trajectories.

Socialization by Known Role Models

Adults, as mentors, teachers, and other prominent figures in young people's lives, are crucial ecological assets in the developmental process and in promoting thriving. The presence of important adults in the lives of youth has been associated with better physical health and well-being (Bryant & Zimmerman, 2003; Véronneau, Koestner, & Abela, 2005), protection against negative adult influences (Hurd, Zimmerman, & Xue, 2009), motivation (Soenens & Vansteenkiste, 2005; Spence & Deci, 2013; Wentzel, 1998), and cognitive, psychological, social, and physical assets (Hamilton et al., 2006). Role models can promote positive development in youth in part through modeling, positive interactions, and emotional support (Bowers et al., 2013; Bowers, Wang, Tirrell, & Lerner, 2016).

The development of character attributes such as purpose (Damon, 2008) are thought to be influenced by adults and peer models who exhibit these attributes. These individuals can be considered role models because they provide a model by which individuals can observe, learn about, and potentially develop their own set of values. In considering development toward prosocial behaviors indicative of character, Carlo and colleagues (2007) demonstrated that positive parenting practices influence youth prosocial behaviors through the development of sympathy for others. In the context of the CABB study, researchers were interested in considering how important adults could promote adolescents' character attributes, in part through prosocial socialization.

A review of socialization literature by Bugental and Grusec (2006) provided a basis for understanding how important adults may use prosocial socialization to impact youth beliefs and behaviors. They wrote that some of our earliest understandings of moral development came from Freud, who focused on the internalization of parental values through discipline and fear of rejection by parents. Freud considered morality to be the superego, which he theorized helps persons to override their instinctual drives toward survival and sex. Bugental and Grusec (2006) then described how, after Freud, Bowlby shifted the study of socialization towards attachment theory – models that involved attachment to caregivers as fostering moral development through warm connections. Subsequent to Bowlby, perspectives emerged advocating for strict behaviorism – learning through action and reinforcement contingencies. In 1963, Bandura and Walters introduced a form of social learning perspective which combined the idea that persons can be reinforced by observed models with the recognition that children can be selective about what they learn from models and can self-regulate towards their own goals. Cultural socialization theory expanded basic socialization to posit that modeling was shaped by and towards goals embedded in the context and culture in which this modeling occurs. Cultural socialization fits well with RDS because this framework pre-supposes that child development is influenced by settings, customs, and belief systems, and that socialization aims to create the best fit between a child and their culture.

In the CABB study, researchers chose to consider character socialization agents of the adolescent's choosing – persons whom the adolescent felt were influential toward their understanding of character, operationalized as "how to be a good person." Asking youth about others who may be involved in their socialization contrasts past studies that have focused on socialization by parents alone (e.g., Carlo et al., 2007). By considering potentially non-parental socialization agents of an adolescent's choosing, CABB researchers moved towards models consistent with RDS, which emphasize the role of the person in their own development as well as the role of context outside of parent-child relationships. Additionally, asking a youth about their perspective on their role models allowed researchers to view the important persons in a youth's life – including, in some cases, parents - that adolescents see as socializing themselves toward prosocial behaviors.

In this dissertation, I examined more closely the aspects of interactions between youth and their character role model that may promote PYD. There is evidence in the literature that supportive and caring relationships with adults can help motivate youth away from negative behaviors and towards positive goals (Kogan, Brody, & Chen, 2011; Theokas & Lerner, 2006). Further, parental conversations, discursive communication, experiential learning, and social rewards with their children (i.e., prosocial socialization) have been shown to promote youth prosocial behaviors by invoking sympathy (Carlo, McGinley, Hayes, Batenhorst, & Wilkinson, 2007). Thus, a close relationship with a caring adult who supports prosocial development through similar types of socialization practices may be beneficial towards the development of character attributes.

The Current Study

Through this dissertation I sought to more fully understand a subset of the multi-faceted construct of character through development of five character attributes, outlined above. Trajectories of character attributes were considered, with the goal of examining whether there was alignment for individuals in terms of classification in optimal character attribute trajectories. To my knowledge there is not a study to this point that examined trajectories of all five of these character attributes together. However, absence of such research is not enough to justify its consideration. Park (2004) provided evidence for the importance of studying groups of character strengths, as defined by Peterson and Seligman (2004), noting that although character strengths alone can be important to thriving and life satisfaction, it is their confluence that can more strongly influence prosocial behavioral outcomes. Park (2004) advocated for future researchers to consider multiple character strengths and their alignment. This dissertation contributed to these aims by considering the development and alignment of a subset of character attributes, many of which are considered character virtues by Peterson and Seligman (2004), in a short period of adolescence. As noted above and in contrast to Peterson and Seligman (2004), these character attributes were not defined as traitlike. In line with RDS principles the attributes are considered to be vulnerable to change based on contextual influences. Thus, in addition to considering their development over a short period in adolescence, the role of the contextual factors ISR and prosocial socialization was considered.

Results from prior research have supported that certain demographic variables, such as sex, are associated with differences in moral affect and behaviors (e.g., Carlo et al., 2007; Hoffman, 1979; Ottoni-Wilhelm et al., 2014; Peterson & Seligman, 2004) such that girls tend to have higher average levels of certain character attributes, and that the differences between boys and girls tends to increase with age (Fabes et al., 1999). As such, sex was considered as a covariate in these analyses.

The following research questions were considered:

1) What is the best-fitting set of trajectories of each attribute for the character sample?

To answer this question, I first determined the structure of the character attributes using confirmatory factor analyses and measurement invariance testing. I then considered changes in levels of each character attribute over three time points. I hypothesized that multiple trajectories would be identified within each character attribute.

2) How does membership in each character attribute trajectory relate to membership in other character attribute trajectories? I hypothesized that optimal levels of character attributes, which I defined as improving or high and relatively consistent levels of each attribute, would be associated with one another (i.e., that participants who exhibit high and stable or increasing levels of one attribute would also be more likely to exhibit the same patterns of other attributes).

3) How is membership in each trajectory associated with ISR, prosocial socialization, and covariates such as sex? I used the responses to these constructs from the initial measurement point (i.e., Wave 2). I hypothesized that that higher levels of ISR and prosocial socialization practices would be associated with optimal character attribute trajectories. Further, I hypothesized that higher levels of ISR and prosocial socialization would be associated with convergence of these optimal trajectories, which would provide evidence that ISR and prosocial socialization can promote confluence of high levels of these character attributes.

Through these analyses, I provided a fuller understanding of a subset of the multi-faceted character system, how the abovementioned character attributes develop within this system, and how contextual factors like ISR and prosocial socialization by known role models may promote membership in optimal character attribute trajectories, typified by high and consistent or increasing levels of each character attribute. This dissertation contributes to the field of adolescent character development by providing empirical evidence for an understanding of the multi-faceted character system from an RDS perspective.

Method

Sampling and Data Collection

Data for this dissertation were drawn from the CABB study (Lerner, Johnson et al., 2013). As detailed above, CABB was a longitudinal mixed-methods study of adolescent character development that took place from Spring 2015 until Spring 2017 in the Northeast U.S. CABB collected data using questionnaires and interviews with youth as well as questionnaires with their parents and school staff. This dissertation included data from the youth questionnaire. The CABB youth questionnaire sample originated from two recruitment methods: an in-school sample and an online sample. The in-school sample was obtained by recruiting schools to take part in the study. Twelve schools agreed to participate in Wave 1 and seven of these schools continued in the study for Waves 2 through 4. Four schools joined the study in Wave 2 and continued through Wave 4. Schools received a $200 gift card for participation in each wave. Individual in-school participant recruitment was conducted by having schools distribute parental permission forms to students. The students' parents or guardians provided consent for their children either online or by returning a paper copy of the consent form. At a time that was convenient for the school, trained research staff collected data from students. Students were asked to assent to participate in the study prior to completing a 45-minute questionnaire. They were told they could skip any questions they did not want to answer and that they could discontinue participation at any time. Students who did not assent to participate returned to their classrooms. If students with parental consent were not present during data collection, they were contacted to complete the survey online or via mail.

In addition to the in-school sample, a second sample of participants was recruited through the online survey company, Qualtrics. The online recruitment procedure began in Wave 2. Qualtrics survey panel members with children aged 11-18 in the Northeast U.S. were recruited and asked to complete an online parental permission form for their child's participation in the CABB study. After parental permission was received by the CABB study, research assistants assessed permission forms to ensure that participants met demographic requirements based on the screening questions (i.e., having a child aged 11-18 in the Northeast U.S.) and then reached out to parents individually to provide a link for their child to complete the questionnaire. Contact information was retained from the parental permission form, and student participants were contacted to complete a new questionnaire during each subsequent wave. Online student participants provided assent and completed the questionnaire, which took about 45 minutes. Students who did not provide assent were taken to a "thank you" page at the end of the questionnaire. All student participants, in both the in-school and online samples, received a $20 gift card for participation in Waves 1, 2, and 3 and a $25 gift card for participation in Wave 4. Analyses for this dissertation include Waves 2 through 4. Wave 1 was excluded from these analyses due to a low overall sample size relative to the other waves and low retention rates between Wave 1 and subsequent waves.

Survey Development

CABB researchers used planned missingness (Graham, Taylor, Olchowski, & Cumsille, 2006) to reduce the length of the questionnaire for individual participants. Using planned missingness meant that participants did not receive full sets of multi-item scales in all cases. Rather, they received about two-thirds of items on multi-item scales with planned missingness. Three forms of the questionnaire were developed so that all items were represented in different combinations. Sections of the questionnaire that were shortened with planned missingness were distributed evenly between the three forms developed. For example, if a scale had three items, one form would have items one and three, the second form would have items two and three, and the third form would have items one and two. See Johnson and colleagues (2016) for a full explanation of the planned missingness design as it pertains to the CABB study. Planned missingness only applied to the in-school survey distribution. Participants who completed the survey at home, online or via mail, had no planned missing items. Approximately 15% of participants in this dissertation's analytic sample (n = 86, 15.58%) had complete case information (i.e., no planned or unplanned missingness) for final preliminary analyses (i.e., preliminary analyses including final items of interest). Approximately one-fifth of participants (n = 103, 18.66%) had complete case information for final analyses with scale scores, completed after preliminary analyses.

In these analyses, planned missingness was observed within the constructs of diligence, future mindedness, humility, intentional self-regulation, and prosocial socialization. There was no planned missingness for honesty or purpose items. Planned missingness ranged from 21.6% to 22.3% for variables of interest in Wave 2, from 22.10% to 24.30% for variables of interest in Wave 3, and from 16.70% to 21.00% for variables of interest in Wave 4. The average percentage of planned missingness on variables of interest was 21.90% in Wave 2, 22.90% in Wave 3, and 19.40% in Wave 4.

Unplanned missingness was observed through participants not completing all items presented or through participants missing participation in one or more waves of data collection. Unplanned missingness was minimal in this dissertation's sample, ranging from 0.00% to 1.10% of responses for variables of interest in Wave 2, from 0.40% to 1.30% of responses for variables of interest in Wave 3, and from 1.60% to 3.00% of responses for variables of interest in Wave 4. The average percentage of unplanned missingness on responses within variables of interest was 0.34% in Wave 2, 0.75% in Wave 3, and 2.31% in Wave 4.

Unplanned missingness in scale scores computed from these variables of interest, used beyond preliminary analyses, was observed for participants who did not complete questionnaires in Waves 3 and/or 4 and for participants who did not complete enough items within each scale for scale scores to be computed. Specifically, there were 552 participants in Wave 2, 456 participants in Wave 3, and 372 participants in Wave 4 with this situation. See preliminary analyses below for details on the number of items required to compute scale scores for each variable.

Unplanned and planned missingness was handled using full information maximum likelihood estimation (FIML) through Mplus Version 7.4 (Muthén & Muthén, 1998-2015). FIML was used to allow planned missingness scores to be predicted based on patterns of individuals’ scores on all other items in the model. FIML allowed for less biased estimations of missing data.

Within all questionnaires (i.e., those with and without planned missingness) items were counterbalanced to ensure equitable distribution. In paper questionnaires, item balancing was accomplished using three different forms in which sets of items were presented in different orders. In online questionnaires, tools within the survey platform (i.e., Qualtrics) were used to randomly order items within the same sets assigned in the paper forms, and the order of these sets was randomly presented.

Participants

Data for Waves 2 through 4 of the CABB study were collected from December 2015 to June 2017. The full Wave 2 student sample included 666 participants, with 419 in-school sample participants and 247 online sample participants. The ages of the full sample in Wave 2 ranged from 9 to 25 years (M = 14.15, SD = 1.98) with 20 participants being missing on age due to a missing date of birth (n = 12), date of survey (n = 8), or both (n = 5). They were in grades 6 through 11. In regard to gender, participants identified as boy (n = 273), girl (n = 384), or another gender (n = 6). Three participants did not provide information on gender. They identified as White, Caucasian, or European American (n = 433), Black, African American, or of African Descent (n = 120), Asian (n = 66), Hispanic or Latino/a (n = 108), Native American/Alaskan Native (n = 9), Arab or Middle Eastern (n = 6), Pacific Islander (n = 7), and another race (n = 17). Seven participants did not provide information on their race/ethnicity. Participants were permitted to identify with more than one race. In later waves, the option "Asian" was changed to "Asian or Asian American" and the option "Caribbean" was added.

Data were screened and cases were removed from the analytic sample based on flags indicating problematic responses. For example, cases were removed if a person answered incorrectly on both attention filter questions (e.g., “Please choose ‘agree’ for this question”; *n* = 18), or if a person responded “Yes” to items that asked if they had not understood the survey (*n* = 3) or not answered truthfully (*n* = 1). Additionally, cases were removed if participants indicated within the questionnaire that they did not attend school in the Northeast U.S. (*n* = 9), which was part of the recruitment criteria. In total, 31 persons were removed due to these flags.

In addition, participants were not included in the analytic sample for several other reasons. The modeling technique used for part of the analyses does not allow for participants to have missing data on predictors and, as such, participants were excluded from the sample if they were missing data on the predictors ISR and prosocial socialization practices (*n* = 74). Additionally, data were screened and cases were removed if the participants did not name a valid *known* role model (e.g., if they named no one *n* = 3, or named a famous individual; *n* = 5). One participant was also removed because they were missing data on all outcomes. Some participants were removed for more than one of these criteria.

The final dataset for this analysis consisted of 552 participants, with 361 of those recruited in schools and 191 recruited online. Three-hundred forty-seven participants completed surveys in all three waves, with 99 participants not completing surveys in Wave 3, 182 participants not completing surveys in Wave 4, and 68 participants not completing surveys in Waves 3 or 4. In this final sample, ages in Wave 2 ranged from 9 to 19 (*M* = 14.11, *SD* = 1.90) with 15 participants being missing on age due to a missing date of birth (*n* = 13), date of survey (*n* = 5), or both (*n* = 3). At Wave 2, they were in grades 6 through 11. Participants identified as boy (*n* = 215), girl (*n* = 331), or another gender (*n* = 5). One participant did not provide information on gender. They identified as White, Caucasian, or

European American (*n* = 356), Black, African American, or of African Descent (*n* = 94), Asian (*n* = 54), Hispanic or Latino/a (*n* = 94), Native American/Alaskan Native (*n* = 6), Arab or Middle Eastern (*n* = 4), Pacific Islander (*n* = 7), and another race (*n* = 15). Two participants did not provide information on their race/ethnicity.

As noted above, in later waves of this survey, items were altered such that "Asian" was changed to "Asian or Asian American" and "Caribbean" was added as an option. As such, the final participants' responses were reviewed and data were cleaned to consider if some participants who identified as "another race" might identify in one of these categories. Based on this screening, a final race/ethnicity variable was created which classified participants as one of the abovementioned races or as multiracial/multiethnic. Seventy-five participants were identified as multiracial/multiethnic. The remaining participants were identified as White, Caucasian, or European American (*n* = 313), Black, African American, or of African Descent (*n* = 56), Asian (*n* = 45), Hispanic or Latino/a (*n* = 57), Arab or Middle Eastern (*n* = 3), and Pacific Islander (*n* = 1). All participants who identified as Native American/Alaskan Native, or Caribbean were identified as Multiracial/Multiethnic. All participants who identified as another race were found to fit better within an existing category or fit within Multiracial/Multiethnic. Looking across these demographic categories, the modal group of participants in this sample identified as White girls who began Wave 2 participation in grades six through eight (i.e., "middle school") through in-school recruitment (*n* = 89). Although this is the modal set of characteristics, it comprises a small percentage of the overall sample (18%), providing some evidence for variation in the sample.

Information on parental demographics were collected via a parent survey. This demographic information was not considered in analyses for this dissertation but is included here to provide further information about the sample. There were 357 parent questionnaires completed for participants in the final sample. The parent sample included parents of students of all races, genders, grades, and recruitment samples identified by the student respondents. Demographic information provided by parents included parental education, income, employment, and relationship status.

Parents reported the following educational levels: less than high school (*n* = 10), GED Certificate/High School Diploma (*n* = 29), vocational/trade school (*n* = 8), some community college (*n* = 25), community college (*n* = 28), some college or university (*n* = 37), 4-year college or university (*n* = 102), some graduate school (*n* = 20), Master's degree (*n* = 63), and PhD or Terminal Degree (*n* = 12). Twenty-three parents did not provide information on educational level.

Parents reported the following annual income: less than $14,999 (*n* = 9), $15,000-29,999 (*n* = 27), $30,000-49,999 (*n* = 40), $50,000-74,999 (*n* = 54), $75,000-99,999 (*n* = 68), greater than $100,000 (*n* = 100). Fifty-nine parents did not provide income information.

Parents reported the following employment information: Not employed and not looking (*n* = 55), not employed and looking for a job (*n* = 10), employed part-time (*n* = 64), employed full-time (*n* = 208). Twenty parents did not provide employment information. Finally, parents provided the following information on their relationship status: Married (*n* = 226), Living with partner (*n* = 22), In a relationship (*n* = 2), Divorced (*n* = 38), Separated (*n* = 10), Widowed (*n* = 9), and Single (*n* = 27). Twenty-three parents did not provide information on their relationship status.

Looking across these demographic categories, the modal group of parents of participants in this sample identified as working full-time with at least a college degree and making at least $75,000 per year who were in a relationship, living with their partner, or married (*n* = 87). This modal sample comprises 24% of the overall parent sample and 16% of the overall sample. The large model sample provided evidence for less variation in overall family income level, parental education levels, work status, and parental relationship status than variation observed in student-reported demographic categories. The restricted variation observed limits the generalizability of the findings of this dissertation. Eighteen participants were in both the student and parent modal set of categories. This is a small percentage of the overall sample (3%). However, it is clear from these demographics that this sample was limited in racial/ethnic and socioeconomic diversity, limiting the generalizability of the results.

Measures

Character Attributes. CABB incorporated several items regarding character attributes to assess the extent to which participants demonstrated character in each wave. As noted above, character attributes to be examined include participant-reported honesty, humility, diligence, future-mindedness, and purpose. These were the key character attributes considered within the CABB study due to their prevalence in the character attribute and character education literature and associations with thriving (Lerner, Johnson, et al., 2013). All items regarding character attributes were considered for inclusion in analyses and were reviewed. See Tables 1 and 2 for the items included in the final analyses. The full items from the survey are available upon request. The process of narrowing items down based on empirical and theoretical fit was considered within the preliminary analyses.

Honesty. To assess participants' honesty, the CABB study researchers adapted an item from the Self-Description III Instrument (Marsh & O'Neill, 1984): "I tell the truth."

Response options ranged from 1 = *Not at all like me* to 5 = *Just like me* for this item. Beginning in Wave 2 of the CABB study, this was the only item used to measure honesty.

Humility. CABB researchers used six items to measure humility with three items measuring intellectual humility and three items measuring general humility. Items were adapted from Porter, Schumann, and Dweck's (2014) scale for measuring intellectual humility. Example items included "I am willing to admit when I do something wrong," "I can learn a lot from other people," and "I am happy for my friends when they win at something, even if it means I lose." Response options ranged from 1 = *Not at all like me* to 5 = *Just like me*.

Diligence. CABB researchers used three items to measure diligence. Two items were adapted from the perseverance of effort subscale from the Short Grit Scale (Duckworth & Quinn, 2009): "I finish whatever I begin" and "I am a hard worker." Researchers developed the third item: "I keep working even when something gets hard." Participants rated how much each statement was like them, with response options from 1 = *Not at all like me* to 5 = *Just like me*.

Future mindedness. CABB researchers used three items adapted from Steinberg and colleagues' (2009) anticipation of future consequences subscale to measure future mindedness. Items were "I think about the consequences of my actions before I do something," "I think about all the possible good and bad things that can happy before making a decision," and "I think about how my decisions will affect others." Response options ranged from 1 = *Not at all like me* to 5 = *Just like me*.

Purpose. CABB researchers adapted 16 items from the Revised Youth Purpose Survey (Bundick et al., 2006), and created one created item. Participants first read the following prompt: “People may have different types of goals for their lives. Below is a list of goals. How important is each goal to you?” Response options ranged from 1 = *Not Important* to 5 = *Extremely Important*. Original items included self-focused and other-oriented goals. Although the focus of this study was other-oriented goals, goals that are theoretically self-oriented can be other-oriented in practice. For example, one of the self-oriented goals considered was "Make money." It is possible that a person may desire to make money in order to contribute to their family. Therefore, both sets of goals were considered together in early stages of estimating the measurement model.

Intentional self-regulation. Self-reported ISR was measured by CABB researchers with nine items adapted from the short-form version (Gestsdóttir et al., 2015) of the Selection, Optimization, and Compensation questionnaire developed by Freund and Baltes (2002). These items were an assessment of the youth’s ability to select goals, optimize resources, and compensate for setbacks in goal achievement. Sample items included “I always pursue goals one after the other,” “When I decide upon a goal, I stick to it,” and “I make every effort to achieve a given goal.” Response options ranged from 1 = *Not at all like me* to 5 = *Just like me*.

Role model presence. CABB participants were asked to name a person who they looked up to as an example of how to be a good person (i.e., character role model). They were specifically asked to focus on persons they interacted with in-person, rather than famous figures. As noted above, participants were screened and removed from the sample if they did not have an appropriate "known" role model upon which to base their responses to the prosocial socialization practice items (n = 8). Responses that were considered inappropriate for this sample included famous figures (n = 2; e.g., Taylor Swift), sports players (n = 3; e.g., Wayne Gretzky), and respondents who did not name a role model (n = 3) because participants could not reasonably answer the questions regarding prosocial socialization if they did not have a personal relationship with their role model. Participants did respond to a separate set of questions about a famous role model, which are not the focus of these analyses.

The final sample of participants named the following people as their known role models in Wave 2: parent (e.g., mother, father, or stepparent; n = 270), friend (e.g., family friend, best friend, neighbor; n = 74), sibling or cousin (n = 67), grandparent (n = 54), adult leader (e.g., teacher, coach; n = 53), or other relative (e.g., aunt, uncle, mother's cousin; n = 34).

Prosocial socialization practices. CABB researchers included six items adapted from a scale originally used to measure the prosocial practices that parents used with their children to measure prosocial socialization of character role models (Parenting Practices Measure [PPM]; Carlo et al., 2007). An example of an original item was “Your mother talks to you about being a moral and responsible person.” The CABB study researchers adapted this item to “Does this person talk to you about how to be a good person?” to be appropriate for youth who did not name their parent as their character role model. All response options were from 0 = *Never* to 4 = *Always*. Aspects assessed included social rewards, moral conversations, experiential learning, and discursive communication.

Data Analysis Plan

The goals of this dissertation included considering trajectories for each character attribute, comparing trajectories of each attribute within persons, and considering how membership in each trajectory and convergence of optimal trajectories was associated with

ISR and prosocial socialization. I estimated models to consider these research questions using Mplus version 7.4 (Muthén & Muthén, 1998-2015) and full information maximum likelihood estimation. See Table 3 for an outline of each research question and associated analyses. A summary of each analysis is reviewed.

Trajectories of Character Attributes

Preliminary analyses, including confirmatory factor analyses (CFAs), invariance testing, and latent curve growth models, were completed prior to growth mixture model estimation to ensure that the growth mixture model was appropriate for the data. Specifically, constructs were determined to appropriately measure the observed data through CFAs and invariance testing. Alternative methods to CFAs and invariance testing were used for honesty because this attribute consisted of only one item. Each character attribute was then confirmed as changing longitudinally on average through latent growth curve models. Growth mixture models were then estimated for each of the character attributes.

Growth mixture modeling was ideal for my research questions because it allowed me to look for overall patterns in the start points and changes in the character attributes while allowing for subgroupings of growth trajectories and variation between individuals within and between these subgroupings. Allowing multiple trajectories within each character attribute addresses the RDS principles of plasticity and interindividual change.

Comparison of Character Attribute Trajectories

Final models were chosen for each character attribute and individual membership in trajectories was compared. Specifically, estimated class parameters (i.e., intercept and slope) were used to calculate predicted start, middle, and end points for each character attribute at the class level. The intercept estimate was used as the predicted start point and the slope estimate was added to calculate the predicted middle and end points. After these estimates were calculated, they were correlated using SPSS version 24.0 to determine whether levels of each attribute were associated with one another within and between time points. Due to the number of patterns observed and the size of the sample, other techniques that could compare categorical memberships between groups, such as a multi-way frequency table, could not be employed in this dissertation.

ISR and Prosocial Socialization as Predictors of Character Attribute Trajectories

ISR and prosocial socialization were then used as predictors of the final models of each character attribute, as well as predictors of the patterns of class membership outcomes between character attributes. These analyses provided evidence for the relation between changes in character attributes with ISR and prosocial socialization.

Results

Preliminary analyses

Prior to creating mean scores for each measure, CFAs were conducted for each construct to ensure that the items considered fit within a scale. Absolute and comparative fit indexes were used to consider model fit for CFAs. Absolute fit indexes provide an understanding of how well a model fits the data absolutely, that is, absent a consideration of any alternative model. The significance value for the chi-square of each model provides the best estimation of model fit in small samples. A nonsignificant chi-square test statistic provides evidence that the model is a good fit to the data. However, in samples with greater than 200 participants, it becomes unlikely that a nonsignificant test statistic is achievable (Kelloway, 2015). As such, alternative absolute fit statistics must be considered. The root mean square error of approximation (RMSEA) and the standardized root mean square residual (SRMR) are two absolute fit statistics based on residual values (i.e., the difference between model-estimated and observed values). They are independent of sample size. An RMSEA value of "below 0.10 is considered a good fit to the data while a value of 0.05 is considered a very good fit to the data" (Kelloway, 2015, p. 25). An SRMR value ranges from 0.0 to 1.0 with a value of less than 0.08 indicating a good fit to the data (Kelloway, 2015).

Comparative fit statistics were also considered. Comparative fit statistics compare models to alternative models with different specified relationships between the indicators. Thus, where the absolute fit indexes compare the specified model to a model with perfect fit to the data (i.e., the observed values), comparative fit statistics compare the model to a model with no specified relationships between the indicators (i.e., the null or baseline model). A comparative fit index (CFI) or Tucker-Lewis fit index (TLI) of greater than 0.95 provide evidence for good fit to the data (Kelloway, 2015). The TLI is used in addition to the CFI because the TLI provides a penalty for model complexity, favoring a more parsimonious model (Kelloway, 2015). In total, the following criteria were used as standards for good fit within a CFA: RMSEA less than 0.10, SRMR less than 0.8, and CFI and TLI greater than or equal to 0.95.

Between-group and longitudinal measurement invariance testing were conducted for each construct to ensure that the same constructs were being measured within the in-school and online-based samples as well as over time. If constructs were found to be measurement invariant in both cases, there would be evidence that the relationship between the items and factors is equivalent between groups and over time. After CFAs were finalized for each construct, models were run that constrained each model progressively to see if there was a significant change in model fit.

For between-group invariance testing, a multiple group CFAs were estimated with the groups being the in-school and online samples. Each model was restricted four times. The first restriction tested for configural invariance (i.e., whether the pattern of factor loadings is the same between groups or longitudinally). The second restriction tested for metric or weak invariance, (i.e., whether the way the item relates to the latent factor is the same between groups or longitudinally). For example, a one-unit higher score on the factor corresponds to a difference in the observed item score in the same way between groups and longitudinally. The third restriction tested for scalar or strong invariance (i.e., whether the expected score on the construct relates to the same expected scores on the items). The fourth restriction tested for residual error or strict invariance (i.e., whether the sum of the item-level variance is the same between groups and longitudinally). All four types of invariance were estimated in all cases, but strict invariance was not considered in deciding whether there was strong enough evidence to assume measurement invariance, as strict invariance is generally considered to be overly restrictive (e.g., Little, 2013).

Differences in model fit were considered through changes in the CFI for all with the addition of chi-square difference tests for longitudinal invariance testing. Changes in CFI or less than or equal to 0.01 were evidence for measurement invariance (Cheung & Rensvold, 2002). Nonsignificant changes in chi-square values provided further evidence for longitudinal measurement invariance. Given that honesty was one item, invariance tests could not be conducted for honesty. Alternative analyses were used to consider differences over time and between groups. Specific information about each analysis is included within each construct. As noted above, final lists of items included in analyses can be found in Tables 1 and 2, and a full list of items in the CABB survey is available upon request. When invariance testing and confirmatory factor analyses provided evidence for a well-fitting measurement model between groups and across time, new scale variables were created using the mean values of each character attribute at each time point.

Character Attribute CFAs and Invariance Testing. Character attributes were modeled as mean scores and trajectories of each attribute were considered, using growth mixture modeling to examine the potential sub-trajectories within each attribute.

Honesty. As honesty was measured using one item, *t*-tests were conducted using SPSS Version 24.0 to consider differences in mean values of this item between the in-school and online samples in each wave. Results demonstrated that mean values of honesty were significantly different between the samples (see Table 4). However, if considering the mean values, the in-school mean value of honesty at each wave was approximately 3.80 and the online sample mean value of honesty in each wave was approximately 4.00. Further, the effect size of the difference, as measured by Cohen's *d*, provided evidence that the practical difference in the means between groups was trivial. As such, samples were not considered separately for subsequent analyses.

Overall, the mean values of honesty at each wave were as follows: Wave 2 $M = 3.85$, $SD = 0.82$, Wave 3 $M = 3.86$, $SD = 0.86$, and Wave 4 $M = 3.90$, $SD = 0.85$. A repeated measures ANOVA was conducted using SPSS Version 24.0 to consider significant differences in mean levels of honesty over time. The overall repeated measures ANOVA test was not significant, indicating no significant mean difference in honesty values longitudinally in the overall sample (see Table 5). This lack of significance provides evidence that honesty can be reliably measured between time points and that the overall sample does not change in their levels of honesty. However, this provides no evidence that honesty cannot exist at different levels or change with subgroups of the sample. Therefore, the results of these analyses provide evidence for use of honesty in subsequent analyses.

Humility. Humility was specified as a one-factor latent model with all six items loading onto one global construct. The one-factor model demonstrated good fit (RMSEA = 0.05, CFI = 0.98, TLI = 0.98, SRMR = 0.02). However, as noted above, the original items for humility included items relating to general humility and openness. The items related to general humility included "I am willing to admit when I do something wrong," "I am happy for my friends when they win at something, even when it means I lose," and "It's okay when someone shows me that I made a mistake." The items related to openness included "I can learn a lot from other people," "I can learn from others even if I disagree with them," and "I am open to changing my ideas." For the purposes of this dissertation, I focused on items that were related to openness and relationships rather than items focused on general humility. As such, a CFA was estimated using the items on the openness scale as well as "It's okay when someone shows me that I made a mistake." This CFA also provided evidence for good fit (RMSEA = 0.74, CFI = 1.00, TLI = 1.01, SRMR < 0.01) and these items were retained for subsequent analyses. Evidence for good fit was also found within Wave 3 (RMSEA = 0.10, CFI = 0.98, TLI = 0.95, SRMR = 0.02) and Wave 4 (RMSEA = 0.00, CFI = 1.00, TLI = 1.00, SRMR = 0.01).

There was evidence for between-group configural, weak, and strong measurement invariance across all three waves of data as well as longitudinal measurement invariance (see Table 6). As such, mean scores were computed for humility within each wave. Based on planned missingness, not all participants completed all four of these items. Responses to at least two items were required to compute a mean score for humility. Overall, the mean values of humility at each wave were as follows: Wave 2 $M = 3.96$, $SD = 0.82$, Wave 3 $M = 3.99$, $SD = 0.81$, and Wave 4 $M = 3.96$, $SD = 0.79$.

Diligence and Future mindedness. As diligence and future mindedness constructs each consisted of three items, these models could not be identified with each construct separately. A confirmatory factor analysis cannot be estimated if the degrees of freedom for the estimated model are zero or less than one. The number of known and unknown parameters in these models resulted in at least four items being necessary for model identification. Given that diligence and future mindedness have the most theoretical similarities of the character attributes considered, CFAs and invariance testing for these constructs were conducted together. Specifically, diligence and future mindedness were estimated as loading onto two latent factors of diligence and future mindedness within one model. This two-factor model demonstrated good fit (RMSEA = 0.04, CFI = 0.99, TLI = 0.98, SRMR = 0.03) and all items were retained for subsequent analyses. Evidence for good fit was also found within Wave 3 (RMSEA = 0.03, CFI = 1.00, TLI = 1.00, SRMR = 0.02) and Wave 4 (RMSEA = 0.00, CFI = 1.00, TLI = 1.00, SRMR = 0.02).

There was evidence for configural, weak, and strong between-group measurement invariance across all three waves of data as well as longitudinal measurement invariance (see Table 7). As such, mean scores were computed for diligence and future mindedness within each wave. These constructs also had planned missingness, and responses to at least two items were required to compute a mean score for each construct. Overall, the mean values of diligence at each wave were as follows: Wave 2 $M = 3.88$, $SD = 0.87$, Wave 3 $M = 3.88$, $SD = 0.90$, and Wave 4 $M = 3.87$, $SD = 0.86$. The mean values of future mindedness at each wave were as follows: Wave 2 $M = 3.63$, $SD = 0.95$, Wave 3 $M = 3.70$, $SD = 0.97$, and Wave 4 $M = 3.74$, $SD = 0.90$.

Purpose. Purpose was specified as a one-factor latent model with all items loading onto one global construct. This one-factor model fit the data poorly in Wave 2 (RMSEA = 0.14, CFI = 0.66, TLI = 0.60, SRMR = 0.10). As noted above, in this original CFA, self- and other-oriented goals were included based on the idea that goals that appear to be self-oriented (e.g., Make money) could, in practice, be other-oriented (e.g., I want to make money so that I can provide for my family). However, based on poor fit when all items were considered together, self-oriented items were removed from the model. Items were also removed based on empirical fit. For example, items were removed if the proportion of variance explained for the item based on the CFA (i.e., *r*-squared value) was less than 0.30 and the item was theoretically more aligned with self-related purpose than other-related purpose.

In subsequent CFAs, items were retained if their *r*-squared value was lower than 0.30 but they were theoretically a strong representation of other-oriented purpose (e.g., "Serve my country"). The final CFA included five items: "Help others," "Do the right thing," "Make the world a better place," "Serve my country," and "Improve my community." This one-factor model fit the data moderately well (RMSEA = 0.15, CFI = 0.93, TLI = 0.87, SRMR = 0.04) and was retained for subsequent analyses. Specifically, the SRMR statistic met the criteria of $< .08$ and the RMSEA statistic was close to the criteria of < 0.10. This model did not meet criteria of $\geqslant 0.95$ for the CFI and TLI.

Lai and Green (2016) wrote that it is rare to find reports of less than 0.90 as accepted in the literature, with the area between 0.90 and 0.95 described as the "gray area between 'good' and 'bad' fit" (p. 224). As noted above, the CFI and TLI statistics measure the amount of departure from close fit. As such, I examined the residual variance of the items to see if any items appeared to have a poor fit within the model. "Serve my country" had a larger residual variance than the other items at 1.06 in the unstandardized model. However, removal of this item did not result in significant improvement to the model. Given the theoretical connection of "Serve my country" to other-oriented purpose and the lack of model improvement with its removal, this item was retained in the final model. There was evidence that this model would have a stronger fit to the data with correlated residual errors between "Help others" and "Do the right thing" and between "Serve my country" and "Improve my community." However, as mean scores would not be able to capture this co-variation, these correlated errors were not specified. I decided to continue with this model given the moderately strong fit and the theoretical connections between the items.

Evidence for moderately good fit was also found within Wave 3 (RMSEA = 0.11, CFI = 0.97, TLI = 0.94, SRMR = 0.03) and Wave 4 (RMSEA = 0.17, CFI = 0.92, TLI = 0.84, SRMR = 0.05). These models continued to demonstrate good fit for the SRMR and close fit for the RMSEA, CFI, and TLI, with the best fitting model in Wave 3.

There was evidence for between-group configural, weak, and strong measurement invariance across Waves 2 and 3 as well as configural and weak longitudinal measurement invariance (see Table 8). The tests of strong measurement invariance in Wave 4 and longitudinally were not met as in both cases the change in CFI was greater than 0.01. The change in CFI for the Wave 4 strong measurement invariance was 0.026 and the change in CFI for the longitudinal strong measurement invariance was 0.011. Cheung and Lau (2012) suggest that the standard for retaining the null of measurement invariance is that the change in CFI should be less than or equal to 0.01. As both of these values are close to this standard, these values were considered evidence for strong measurement invariance in both cases. Given that 0.026 was further away from this standard, observed mean values and their variances were examined between the school and online samples. Differences in overall mean values ranged from 0.01 for "Do the right thing" to 0.54 for "Serve my country." Differences in variances ranged from 0.05 for "Help others" to 0.12 for "Do the right thing." Given that the differences in the means and variance did not amount to a large practical difference for any items (i.e., less than a one-point difference) the measures were considered practically invariant. Additionally, given that substantive differences between the groups were not of interest in this dissertation, partial invariance was considered sufficient for computing scale scores for purpose. There was no planned missingness for purpose items, and so responses to all five items were required to compute a mean score. Overall, the mean values of purpose at each wave were as follows: Wave 2 M = 3.99, SD = 0.75, Wave 3 M = 3.95, SD = 0.76, and Wave 4 M = 3.95, SD = 0.76.

Intentional self-regulation CFA and Invariance Testing. Previously, researchers have found that a one-factor model tends to fit ISR data best in early adolescence and a three-factor model fits ISR data best as youth approach adulthood (Gestsdóttir & Lerner, 2007; Gestsdóttir et al., 2009). However, more recently researchers have found that a one-factor model is a better representation of ISR across adolescence (Gestsdóttir et al., 2015). Two different models were specified and compared to determine the best fit for ISR. One model had all items loading onto one global factor and the other had items loading onto the constructs of Selection, Optimization, and Compensation (i.e., SOC).

The three-factor model was empirically unable to be identified because there was a correlation of greater than one between two latent factors. This result meant that the three-factor model was not a good fit for ISR because the three factors specified did not represent substantively different constructs. The one-factor model demonstrated good fit (RMSEA = 0.07; CFI = 0.96; TLI = 0.95; SRMR = 0.04). There was evidence that the model would have a stronger fit to the data with correlated residual errors. However, as mean scores would not be able to capture this co-variation, these correlated errors were not specified.

There was evidence for configural, weak, and strong between-group measurement invariance within wave two (see Table 9). As such, mean scores were computed for ISR within Wave 2. The ISR scale had planned missingness and therefore responses to six items were required to compute a mean score for the construct. The mean value for intentional self-regulation was 3.79, *SD* = 0.80.

Prosocial Socialization Practices CFA and Invariance Testing. The construct of prosocial socialization practices was specified as a one-factor latent model with all items loading onto one global construct. The one-factor model demonstrated good fit (RMSEA = 0.05; CFI = 0.99; TLI = 0.98; SRMR = 0.02). However, two items stood out as having a weak fit to the overall factor based on lower factor loadings and theoretical mis-match. The first item, "Does this person praise you or show you love when you help someone?" stood out as incorporating social rewards, and the other items included were more related to conversations and encouragement. The other item that stood out, "Does this person talk to you about what you can learn from TV shows/books/movies about how to be a good person?' had a very high residual variance compared to the others in the set. This item stood out as incorporating media into conversations, whereas other items did not specifically include modeling through media. When these items were removed, there was evidence for better model fit (RMSEA = 0.00; CFI = 1.00; TLI = 1.01; SRMR < 0.01). This model was retained for subsequent analyses.

There was evidence for configural, weak, and strong between-group measurement invariance within wave two (see Table 9). As such, mean scores were computed for prosocial socialization within Wave 2 using four items. The prosocial socialization scale had planned missingness, and therefore responses to three items were required to compute a mean score for the construct. The mean value for prosocial socialization was 2.96, *SD* = 0.94.

Character Attribute Latent Growth Curve Models. The goal of the first research question for this dissertation was to examine subgroups of trajectories for each character attribute. The purpose of examining these subgroups of trajectories was to appropriately account for the RDS principles of plasticity and interindividual differences in youth character development. Preliminary analyses including CFAs and invariance testing provided a solid foundation for conducting growth mixture models. However, subgroups of trajectories cannot be examined without estimating appropriately fitting non-mixture (i.e., one-class) latent growth curve models (Masyn, 2018). As such, latent growth curve models were estimated for each character attribute. All character attribute scale scores had the potential to range between 1 and 5. Intercept values were considered *low* if they were lower than 3, *moderate* if they were between 3 and 4, and *high* if they were above 4.

Honesty. Absolute and relative indices for the unconditional linear latent growth curve indicated that the model was a good fit for the data (RMSEA = 0.00, CFI = 1.00, TLI = 1.01, SRMR < 0.01). The average value for honesty at the first measurement occasion was 3.83 on a 5-point scale, which indicated a moderate overall score on honesty in Wave 2. The slope estimate indicated that between each measurement occasion, self-reported honesty increased by 0.04 points on average. The slope estimate was not significantly different from zero ($p = .12$) which indicated that there was not a significant change in honesty longitudinally for the overall sample. The variance for the baseline estimate was significant ($p < .001$), which indicated significant individual variation from the average baseline score. Variance for the slope estimate was not significant ($p = .25$) which indicated that there was not significant individual variation in the average slope. There was not a significant covariation between the intercept and the slope of this model ($p = .33$).

Humility. Absolute and relative indices for the unconditional linear latent growth curve indicated that the model was a good fit for the data (RMSEA = 0.01, CFI = 1.00, TLI = 1.00, SRMR = 0.01). The average value for humility at the first measurement occasion was 3.96 on a 5-point scale, which indicated a moderate overall score on humility in Wave 2. The slope estimate indicated that between each measurement occasion, self-reported humility increased by less than 0.01 points on average. The slope estimate was not significantly different from zero ($p = .84$) which indicated that there was not a significant change in humility longitudinally for the overall sample. Variance for the baseline estimate was significant ($p < .001$), which indicated significant individual variation from the average baseline score. Variance for the slope estimate was also significant ($p = .001$) which indicated that there were individuals for whom there was a change in humility. There was a significant negative covariation between the intercept and the slope of this model ($p < .001$), which provided evidence that a higher baseline value of humility was associated with a lower slope and the converse.

Diligence. Absolute and relative indices for the unconditional latent growth curve indicated that the model was a good fit for the data (RMSEA = 0.00, CFI = 1.00, TLI = 1.01, SRMR < 0.01). The average value for diligence at the first measurement occasion was 3.88 on a 5-point scale, which indicated a moderate overall score on diligence in Wave 2. The slope estimate indicated that between each measurement occasion, self-reported diligence decreased by less than 0.01 points on average. The slope estimate was not significantly different from zero ($p = .97$) which indicated that there was not a significant change in diligence longitudinally for the overall sample. Variance for the baseline estimate was significant ($p < .001$), which indicated significant individual variation from the average baseline score. Variance for the slope estimate was also significant ($p = .02$) which indicated that there were individuals for whom there was a change in diligence. There was a significant negative covariation between the intercept and the slope of this model ($p = .03$), which provided evidence that a higher baseline value of diligence was associated with a lower slope and the converse.

Future mindedness. The unconstrained latent growth model could not be estimated due to a lack of variance in slope across the sample. The model estimated appropriately when the variance in slope was constrained to zero, which also constrained the covariation between the baseline level and the slope to be zero. With these restrictions, absolute and relative indices for the unconditional latent growth curve indicated that the model was a good fit for the data (RMSEA = 0.00, CFI = 1.00, TLI = 1.01, SRMR = 0.02). The average value for future mindedness at the first measurement occasion was 3.64 on a 5-point scale, which indicated a moderate overall score on future mindedness in Wave 2. The slope estimate indicated that between each measurement occasion, self-reported future mindedness increased by 0.05 points on average. The slope estimate was not significantly different from zero (p = .05) indicating that there was not a significant change in future mindedness longitudinally for the overall sample. Variance for the baseline estimate was significant (p < .001), which indicated significant individual variation from the average baseline score. As noted above, variance for the slope estimate and the covariation between the intercept and slope estimates were fixed to zero for model identification.

Purpose. Absolute and relative indices for the unconditional latent growth curve indicated that the model was a good fit for the data (RMSEA = 0.00, CFI = 1.00, TLI = 1.01, SRMR < 0.01). The average value for purpose at the first measurement occasion was 3.99 on a 5-point scale, which indicated a moderate overall score on purpose in Wave 2. The slope estimate indicated that between each measurement occasion, self-reported purpose decreased by 0.05 points on average. The slope estimate was significantly different from zero (p < .01) which indicated that there was a significant change in purpose longitudinally for the overall sample. Variance for the baseline estimate was significant (p < .001), which indicated significant individual variation from the average baseline score. Variance for the slope estimate was also significant (p = .01) which indicated that there were individuals for whom there was a different change in purpose. There was a significant negative covariation between the intercept and the slope of this model (p < .01), which provided evidence that a higher baseline value of purpose was associated with a decreasing slope and the converse.

Trajectories of Character Attributes

As described above, well-fitting latent growth curve models were estimated for every character attribute as the final preliminary step needed to answer the first research question, regarding the different trajectories of character attributes within persons. The latent growth curve models largely provided evidence for moderate levels of each character attribute in the overall sample, with evidence for change in future mindedness and purpose. However, the change in these attributes was only approximately 0.05 between each wave.

There was significant variation in the baseline estimates for every attribute, which indicated that there was significant individual variation from the mean in baseline levels of all character attributes. There was significant variation in the slope estimates for humility, diligence, and purpose, providing evidence that there were individuals for whom the change in these character attributes was significantly different from the mean estimates for each slope. These significant deviations from the overall parameters provided evidence that character attributes may be better considered through growth mixture modeling because this technique allows for subgroups of intercepts and slopes within each attribute. Thus, trajectories of each attribute were examined using growth mixture modeling to consider whether heterogeneous subgroups could be identified within the sample in regard to trajectories of each attribute.

The analysis plan for growth mixture models was constructed following recommendations from Masyn (2013, 2018). First, I conducted model building by estimating models for each attribute with increasing numbers of classes (i.e., class enumeration) within five possible variance-covariance structures. The variance-covariance structures considered were latent class growth analysis, diagonal and class-invariant, non-diagonal and class-varying, diagonal and class-varying, and non-diagonal and class-varying. These variance-covariance specifications can be understood as follows:

Within latent class growth analyses, the variance of the intercept and slope and covariation between the intercept and slope are constrained to zero in all classes. Differences between classes are based solely on differences in mean levels of intercept and slope.

Within a diagonal and class-invariant specification, the covariation between the intercept and slope are constrained to zero and the variance of the intercept and the slope are constrained to be the same in all classes, while mean values of intercept and slope are permitted to vary. Within a non-diagonal and class-invariant specification, the covariation between the intercept and slope and the variance in the intercept and the slope are estimated but constrained to be equal across classes.

The diagonal and class-varying specification uses the diagonal specification of the covariation between the intercept and the slope being fixed to zero, but allows the variances estimated to vary between classes. The non-diagonal and class-varying specification uses the non-diagonal specification where the covariation between the intercept and the slope is estimated, but allows the variances estimated to vary between classes.

Class enumeration was conducted for each variance-covariance structure until the log-likelihood values would no longer converge, which provided evidence that the model was no longer a good fit for the data. The maximum start values used were 10,000 initial stage starts and 1,000 final stage optimizations. There was evidence for a lack of model fit if the maximum start values used did not result in a replication of the best log-likelihood value or if a lack of variance in the manifest variables did not allow for the model to be estimated.

For each set of models estimated, the best models within each variance-covariance specification were compared. Absolute fit statistics (e.g., the RMSEA) are not currently available for growth mixture modeling. Relative fit criteria were used for model comparison including the Bayesian Information Criteria (BIC), Consistent Akaike's Information Criteria (CAIC), Approximate Weight of Evidence Criterion (AWE), adjusted Lo-Mendell-Rubin-Likelihood Ratio Test (LMR-LRT) *p*-value, approximate Bayes Factor (BF), and correct model probability (cmP). The Akaike Information Criteria (AIC), bootstrap likelihood ratio test (BLRT) *p*-values, and entropy values were estimated but were not included in the final tables because they did not provide useful information for model selection (e.g., the AIC was largely observed to consistently decrease and BLRT *p*-values were almost always significant).

The best model fit for BIC, CAIC, and AWE statistics is demonstrated in class enumeration when plots of these values stop consistently decreasing (i.e., when the profiles of each become flat with increasing classes rather than continuing to noticeably decrease). The minimum goodness-of-fit criteria are the values associated with the one-class, class-invariant, nondiagonal specification. In order to be considered as a strong model, the model must meet the minimum criteria set for each by this one-class class-invariant, non-diagonal specification. The adjusted LMR-LRT *p*-value provided information as to whether the model was significantly improved from the previous model with the same specifications and fewer classes. The approximate BF provided information as to the likelihood of the model being correct compared to the previous model with one fewer class. Within the class enumerations conducted, some model specifications had to be restricted for model identification purposes. As such, the adjusted LMR-LRT *p*-values and approximate BF values provided for each model may not represent the differences between the estimated models, as the exact same restrictions were not in place for every model estimation. Specific model restrictions are noted within summaries of class enumerations for each construct. Finally, the cmP was calculated for all models within each variance-covariance structure. The cmP provided an estimate of the likelihood that each model within the variance-covariance structure was the correct model, under the assumption that the correct model was one of the models being compared. For example, if the estimated cmP for a model is .90, this means that there is 90% chance that this model is the correct model assuming that the correct model is within the set of models compared.

Examination of each piece of evidence supported the decision for the most appropriate model within each variance-covariance specification. After the best model was chosen within each specification, the cmP was re-estimated between specifications. Previously estimated fit criteria, theoretical considerations, and these cmP values were used to select two candidate models for each character attribute. Further comparisons were conducted between candidate models by estimating their classification diagnostics. Specifically, model-estimated class proportions were used to estimate the modal class assignment proportion (mcaP), average posterior class probability ($AvePP_k$), and odds of correct classification ratio (OCC_k) for each class within each model. These statistics provided evidence for class assignment accuracy based on posterior class probabilities. The model-estimated class proportions are the estimated proportions for each class based on model estimates. The mcaPs are the proportion of individuals that would be modally assigned to each class. The model-estimated class proportions and the mcaPs would be equal if individuals were assigned to classes with no uncertainty. A large discrepancy between these statistics indicates errors in class assignments. The $AvePP_k$ is the mean of the posterior class probabilities for all individual assigned to that class. The OCC_k is the odds that someone is correctly classified in the class to which they are assigned. $AvePP_k$ estimates above .70 and OCC_k estimates greater than five provide evidence that there is good separation and accurate class assignment in each model (Masyn, 2013).

Final models for each character attribute were chosen based on empirical and theoretical considerations. For example, a model with two classes that were not well separated was not chosen as a final model because this violated the theoretical and empirical assumptions that there would be multiple, well-separated classes. Within each final model, model-estimated class proportions, parameter estimations, and standard errors were considered to support substantive class interpretations. Final models for each character attribute were bolded within each class enumeration table. Classes within each model were characterized as being *low*, *moderate*, or *high* and as decreasing, relatively consistent, or increasing. As with LCGMs above, baseline estimates were low if they were lower than 3, moderate if they were between 3 and 4, and high if they were above 4. Trajectories were characterized as increasing or decreasing if they had a slope that was significantly different from zero and positive or negative, respectively. Trajectories were characterized as relatively consistent if slopes were not significantly different from zero.

Honesty. I was able to estimate models with up to 7 classes within the LCGA specification, up to 9 classes within the diagonal class-invariant specification, and only 1 class within the remaining specifications (models with the remaining specifications with 2 or more classes did not converge). The relative fit statistics described above were included in Table 10. Figure 2 displays plots which were used to determine the point at which the information criteria were best within each variance-covariance structure. Plots include the LCGA and diagonal class-invariant specifications as the other specifications were only estimated for up to one class. The dotted line in each plot is the minimum goodness of fit line. These plots provided evidence that relative fit criteria significantly decreased from the five-class to the six-class models in both the LCGA and the diagonal and class-invariant specifications, and increased after this point. In both cases, the adjusted LMR-LRT *p*-value did not indicate significantly better fit than one fewer class. However, the steep decline in log-likelihood value in both cases provided evidence that the six-class model was a better fit to the data. Additionally, the cmP value calculated within each variance-covariance specification provided evidence that the six-class models were the best fit for both specifications.

The six-class model for the LCGA and diagonal and class-invariant specifications and the one-class model for the remaining specifications were used to compute the cmP values across specifications. The cmP value for the LCGA specification was 0.91, providing strong evidence for this model as the final model. Masyn (2013) recommended that two candidate models be considered for further analysis. As such, the six-class LCGA and the six-class diagonal and class-invariant models were considered further. The model-estimated class proportions were used to estimate the mcaP, $AvePP_k$, and OCC_k for each class within these candidate models. The details of these estimations are included in Tables 11 and 12. Classes are labeled by numbers as substantive class interpretations were not officially assigned at that point in the class enumeration process. In both models, the similarities between the model-estimated class proportions and the mcaP provided evidence that individuals in each class were well-classified. All $AvePP_k$ estimates were above .70 and all OCC_k estimates were greater than five, which provided evidence that there was good separation and accurate class assignment in each model (Masyn, 2013). These comparisons demonstrated that both models were solid in class assignment and separation between classes but did not provide enough evidence to decide which model is a better fit to the data.

Model estimated within-class baseline estimates and slopes were considered for additional evidence. As the diagonal class-invariant specification needed to be restricted with the variance of the slope at zero for model identification, the variance in intercept estimates was considered. The variance in the intercept estimates was 0.002 and was not significantly different from zero (p = 0.16). These estimates provided evidence that there was not a significant variation in baseline estimates for the diagonal class-invariant specification, and therefore that the LCGA, which explicitly restricted this parameter to zero, was a better fit for the model. As such, the six-class LCGA was selected as the final model for honesty.

Model-estimated class proportions and within-class means were considered within the final model to support substantive class interpretation. As the final model specification restricted the variance of estimated parameters to zero, variance in these parameters was not considered for class interpretation. Parameter estimations are included in Table 13. The majority of individuals in the sample were classified into three of the classes, providing evidence that there is no significant majority class. The three majority classes included 42.70%, 25.00%, and 21.92% of the sample. Based on intercept and slope estimates, the initial majority class was characterized by a trajectory of high and relatively consistent honesty, the second majority class was characterized by a trajectory of moderate and increasing honesty, and the third majority class was characterized by a trajectory of high and decreasing honesty. The remaining three classes included 1.45%, 2.90%, and 5.98% of the sample. They were characterized by trajectories of high honesty that was decreasing more steeply, moderate and relatively consistent honesty, and low and increasing honesty, respectively. Table 13 provides the intercept and slope information for each class and Figure 7 provides a visual plot which includes honesty trajectories for each class.

Humility. I was able to estimate up to 8 classes within the LCGA specification, up to 7 classes within the diagonal class-invariant specification, up to 4 classes within the non-diagonal and class-invariant specification, up to 2 classes within the diagonal and class-varying specification, and only 1 class within the non-diagonal and class-varying specification. The relative fit statistics described above were included in Table 14. Figure 3 displays plots which were used to determine the point at which the information criteria were best within each variance covariance structure. The non-diagonal class-varying specification was not included in these plots as only one class could be estimated. The dotted line in each plot is the minimum goodness of fit line. These plots provided evidence that most relative fit criteria decreased across class enumerations in every variance-covariance specification. There was not a point at which they declined to decrease significantly. Adjusted LMR-LRT *p*-values indicated that additional classes declined to improve model fit at 4 classes for the LCGA, 3 classes for the diagonal class-invariant specification, 2 classes for the non-diagonal class-invariant specification, and 1 class for the diagonal class-varying specification. The cmP values calculated within each variance-covariance specification provided evidence for the following models as the best fit: 6 classes within the LCGA, 7 classes within the diagonal and class-invariant specification, 4 classes within the non-diagonal and class-invariant specification, 2 classes within the non-diagonal and class-varying specification, and 1 class within the non-diagonal and class-varying specification. In all cases, the adjusted LMR-LRT *p*-value did not provide evidence for significantly better fit than one fewer class.

However, all additional relative fit statistics provided evidence for good fit relative to the other model estimations.

The cmP values were computed between specifications for the best model fit between variance-covariance specifications and the two models with the best cmP value were selected as candidate models for further analysis. These were the six-class LGCA and the seven-class diagonal and class-invariant models. The model-estimated class proportions were used to estimate the mcaP, $AvePP_k$, and OCC_k for each class within these candidate models. The details of these estimations are included in Tables 15 and 16. Classes are labeled by numbers as substantive class interpretations were not officially assigned at that point in the class enumeration process. In both models, the similarities between the model-estimated class proportions and the mcaP provided evidence that individuals in each class are well-classified. All $AvePP_k$ estimates were above .70 and all OCC_k estimates were greater than five, which provided evidence that there was good separation and accurate class assignment in each model (Masyn, 2013). These comparisons provided evidence that both models are solid in class assignment and separation between classes and did not provide enough evidence for which model is a better fit to the data.

Model estimated within-class baseline estimates and slopes were considered. As the diagonal class-invariant specification needed to be restricted with the variance of the slope at zero for model identification, the variance in intercept estimates was considered. The variance in the intercept estimates within this model was 0.03 and was significantly different from zero ($p < .01$). This significant variance in intercept estimates provided evidence that there may be significant variation in baseline estimates in this sample, which was not permitted within the LCGA specification. However, comparison of initial relative fit statistics provided evidence for better overall model fit in the six-class LCGA model. For example, the cmP value between specifications indicated that, if the final models within each variance-covariance specification included the correct model, there was an 85% chance that the six-class LCGA was the correct model. Additionally, the BIC and AWE values were stronger in the six-class LCGA model. As such, the six-class LCGA model was selected as the final model for humility.

Model-estimated class proportions and within-class means were considered within the final model to support substantive class interpretations. As the final model specification restricted the variance of estimated parameters to zero, variance in these parameters was not considered for class interpretation. Parameter estimations are included in Table 17. The majority of individuals in the sample were classified into three of the classes, which provided evidence that there is no significant majority class. The three majority classes included 32.97%, 34.78%, and 21.92% of the sample. Based on intercept and slope estimates, the initial majority class was characterized by a trajectory of high and decreasing humility, the second majority class was characterized by a trajectory of moderate and increasing humility, and the third majority class was characterized by a trajectory of moderate and relatively consistent humility. It should be noted that the class characterized by high and decreasing humility had a significantly negative slope, but the 95% confidence interval around this slope estimate ranged from negative to positive (see Table 17). This means that this class is relatively consistent, with only a slight decrease in humility. For ease of interpretation it will be referred to as the high and decreasing class, given that there is a significant slope value. The remaining three classes included 3.26%, 6.34%, and 0.72% of the sample. They were characterized by trajectories of high humility that was decreasing more steeply, low and increasing humility, and low and relatively consistent humility, respectively. Table 17 provides the intercept and slope information for each class and Figure 8 provides a visual plot which includes humility trajectories for each class.

Diligence. I was able to estimate up to 11 classes within the LCGA specification, up to 7 classes within the diagonal class-invariant specification, up to 3 classes within the non-diagonal and class-invariant specification, up to 2 classes within the diagonal and class-varying specification, and only 1 class within the non-diagonal and class-varying specification. The relative fit statistics described above were included in Table 18. Figure 4 displays plots which were used to determine the point at which the information criteria were best within each variance covariance structure. The non-diagonal class-varying specification was not included in these plots because only one class could be estimated. The dotted line in each plot is the minimum goodness of fit line. These plots provided evidence that most relative fit criteria decreased and then increased across class enumerations. Adjusted LMR-LRT *p*-values provided evidence that additional classes did not improve model fit beginning at 4 classes for the LCGA, 3 classes for the diagonal class-invariant specification, and 3 classes for the non-diagonal class-invariant specification. The cmP values calculated within each variance-covariance specification provided evidence for the following models as the best fit: 4 classes within the LCGA, 2 classes within the diagonal and class-invariant specification, 2 classes within the non-diagonal and class-invariant specification, 2 classes within the non-diagonal and class-varying specification, and 1 class within the non-diagonal and class-varying specification. In most of these cases, the adjusted LMR-LRT *p*-value did not provide evidence for significantly better fit than one fewer class. However, most additional relative fit statistics provided evidence for good fit relative to the other model estimations.

The cmP values were computed between specifications for the best model fit between variance-covariance specifications and the two models with the best cmP values were selected as candidate models for further analysis. These were the four-class LGCA and the two-class diagonal and class-invariant models. The model-estimated class proportions were used to estimate the mcaP, $AvePP_k$, and OCC_k for each class within these candidate models. The details of these estimations are included in Tables 19 and 20. Classes are labeled by numbers as substantive class interpretations were not officially assigned at that point in the class enumeration process. In both models, the similarities between the model-estimated class proportions and the mcaP provided evidence that individuals in each class were relatively well-classified. However, based on differences in these values within classes, there was evidence that the participants in the two-class diagonal class-invariant model were less well classified than the participants in the four-class LCGA model. All $AvePP_k$ estimates were above .70. OCC_k estimates were all greater than five in the four-class LCGA model, which provided evidence that there is good separation and accurate class assignment in this model (Masyn, 2013). One OCC_k estimate in the two-class diagonal and class-invariant model was less than five, suggesting poor class separation and inaccurate class assignment in this model. These comparisons provided evidence the four-class LCGA model was a better fit to the data. As such, the four-class LCGA model was selected as the final model for diligence.

Model-estimated class proportions and within-class means were considered within the final model to support substantive class interpretations. As the final model specification restricted the variance of estimated parameters to zero, variance in these parameters was not considered for class interpretation. Parameter estimations are included in Table 21. The majority of individuals in the sample were classified into one of the classes, providing evidence that there is a majority class. However, this majority class included only slightly over half of the sample (52.17%), which indicated that parameter estimates are a better consideration for substantive model interpretation (i.e., that this class should not be labeled "average"). The majority class was characterized by a trajectory of high and relatively consistent diligence. The remaining classes included 9.96%, 4.35%, and 33.51% of the sample. These classes were characterized by trajectories of low and increasing, high and decreasing, and moderate and increasing diligence, respectively. Table 21 provides the intercept and slope information for each class and Figure 9 provides a visual plot of diligence trajectories for each class.

Future mindedness. One participant was not included in these analyses due to missing data on future mindedness at all time points. I was able to estimate up to 7 classes within the LCGA specification, up to 8 classes within the diagonal class-invariant specification, up to 3 classes within the diagonal and class-varying specification, and no classes within the non-diagonal specifications. The relative fit statistics described above were included in Table 22. Figure 5 displays plots which were used to determine the point at which the information criteria were best within each variance covariance structure. These plots only included specifications for which more than one class could be estimated. The dotted line in each plot is the minimum goodness of fit line. These plots provided evidence that most relative fit criteria decreased and then increased across class enumerations. Adjusted LMR-LRT *p*-values provided evidence that additional classes declined to improve model fit at 5 classes for the LCGA and 2 classes for the diagonal class-invariant specification. The cmP values calculated within each variance-covariance specification provided evidence for the following models as the best fit: 4 classes within the LCGA, 2 classes within the diagonal and class-invariant specification, 2 classes within the non-diagonal and class-invariant specification, 2 classes within the non-diagonal and class-varying specification, and 1 class within the diagonal and class-varying specification. The adjusted LMR-LRT *p*-value provided further evidence for significantly better fit than one fewer class for the LCGA and diagonal and class-invariant models.

The cmP values were computed between specifications for the best model fit between variance-covariance specifications and the two models with the best cmP values were selected as candidate models for further analysis. These were the four-class LGCA and the two-class diagonal and class-invariant model. The model-estimated class proportions were used to estimate the mcaP, $AvePP_k$, and OCC_k for each class within these candidate models. The details of these estimations are included in Tables 23 and 24. Classes are labeled by numbers as substantive class interpretations were not officially assigned at that point in the class enumeration process. In both models, the similarities between the model-estimated class proportions and the mcaP provided evidence that individuals in each class were relatively well-classified. Based on differences in these values within classes, there was evidence that the participants in two-class diagonal class-invariant model were less well classified than the participants in the three of the four classes within the four-class LCGA. All $AvePP_k$ estimates were above .70. OCC_k estimates were greater than five in the three of the four classes in the four-class LCGA model, providing evidence that there was relatively good separation and accurate class assignment in this model (Masyn, 2013). One of the two

OCC_k estimates in the two-class diagonal and class-invariant model is less than five, providing evidence for poor class separation and inaccurate class assignment in this model. Overall, these comparisons provided evidence that the four-class LCGA had a stronger fit to the data in terms of similarities between model-estimated class proportions and mcaPs in terms of OCC_k values. Given these comparisons, I selected the four-class LCGA model as the final model for future mindedness.

Model-estimated class proportions and within-class means were considered within the final model to support substantive class interpretations. As the final model specification restricted the variance of estimated parameters to zero, variance in these parameters was not considered for class interpretation. Parameter estimations are included in Table 25. The majority of individuals in the sample were classified into two of the classes, providing evidence that there is no majority class. The two majority classes included 45.01% and 36.12% of the sample and were characterized by trajectories that were moderate and increasing and high and relatively consistent in future mindedness, respectively. The remaining classes included 3.45% and 15.43% of the sample. These classes were characterized by trajectories that were high and decreasing and low and increasing on future mindedness. Table 25 provides the intercept and slope information for each class and Figure 10 provides a visual plot which considers changes in future mindedness for each class.

Purpose. Three participants were not included in these analyses due to missing data on purpose at all time points. I was able to estimate up to 14 classes within the LCGA specification, up to 5 classes within the diagonal class-invariant specification, up to 3 classes within the diagonal and class-varying specification, and only 1 class within each class-varying specification. The relative fit statistics described above were included in Table 26.

Figure 6 displays plots which were used to determine the point at which the information criteria were best within each variance covariance structure. The class varying specifications were not included in the plots as only one class could be estimated for each. The dotted line in each plot is the minimum goodness of fit line. These plots provided evidence that most relative fit criteria decreased and then increased across class enumerations in the LCGA and diagonal and class-invariant specifications and that they decreased consistently between class enumerations for the non-diagonal class-invariant specification. Adjusted LMR-LRT *p*-values provided evidence that additional classes declined to improve model fit at 3 classes for the LCGA and 2 classes for the diagonal class-invariant specification. The cmP values estimated within each variance-covariance specification provided evidence for the following models as the best fit: 6 classes within the LCGA, 2 classes within the diagonal and class-invariant specification, and 3 classes within the non-diagonal and class-invariant specification.

The cmP values were computed between specifications for the best model fit between variance-covariance specifications and the two models with the best cmP values were selected as candidate models for further analysis. These were the six-class LGCA and the three-class non-diagonal and class-invariant models. The model-estimated class proportions were used to estimate the mcaP, $AvePP_k$, and OCC_k for each class within these candidate models. The details of these estimations are included in Tables 27 and 28. Classes are labeled by numbers as substantive class interpretations were not officially assigned at that point in the class enumeration process. In both models, the similarities between the model-estimated class proportions and the mcaP provided evidence that individuals in each class were relatively well-classified. Most $AvePP_k$ estimates were above .70 with the exception of class

6 within the six-class LCGA, which was .69. OCC_k estimates were all greater than five, which provided evidence that there is relatively good separation and accurate class assignment in these models (Masyn, 2013).

Overall, these comparisons provided evidence that each model fits the data similarly well. As such, parameter estimates were considered for further evidence. The variance in the intercept estimates for the three-class non-diagonal and class-invariant specification was 0.06 and was not significantly different from zero ($p = .16$). The variance in the slope estimates for this model was 0.03 and was not significantly different from zero ($p = .16$). These estimates provided evidence that there is not significant variation in baseline or slope estimates in this sample. As such, the six-class LCGA model was selected as the final model for purpose.

Model-estimated class proportions and within-class means were considered within the final model to support substantive class interpretations. As the final model specification restricted the variance of estimated parameters to zero, variance in these parameters was not considered for class interpretation. Parameter estimations are included in Table 28. The majority of individuals in the sample were classified into three of the classes, providing evidence that there was no majority class. The three majority classes included 24.95%, 32.34%, and 24.23% of the sample. These classes were characterized by trajectories that were moderate and increasing, high and decreasing, and high and increasing on purpose, respectively. It should be noted that the class characterized by high and increasing purpose had a significantly positive slope, but the 95% confidence interval around this slope estimate ranged from negative to positive (see Table 28). This means that this class is relatively consistent, with only a slight increase in purpose. For ease of interpretation it will be referred to as the high and increasing class, given that there is a significant slope value. The remaining classes included 12.20%, 5.46%, and 0.91% of the sample. These classes were characterized by trajectories that were high and decreasing more steeply, low and relatively consistent, and low and increasing on purpose, respectively. Table 28 provides the intercept and slope information for each class and Figure 11 provides a visual plot which considers changes in purpose for each class.

Comparison of Character Attribute Trajectories

Taken together, final models for each character attribute were all LCGAs, meaning that the mean values of intercept and slope were permitted to vary between classes but that the variance of the intercept and the slope as well as the covariation between intercept and slope were restricted to zero within each class. The final models for honesty, humility, and purpose included six classes, whereas the final models for diligence and future mindedness included four classes (see Figures 7-11). The final model for honesty included trajectories that were high and relatively consistent (42.75%), moderate and increasing (25.00%), high and decreasing more steeply (1.45%), high and decreasing (21.92%), moderate and relatively consistent (2.90%), and low and increasing (5.98%) (see Table 13 and Figure 7). The final model for humility included trajectories that were high and decreasing (32.97%), moderate and increasing (34.78%), high and decreasing more steeply (3.26%), low and increasing (6.34%), low and relatively consistent (0.72%), and moderate and relatively consistent (21.92%) (see Table 17 and Figure 8). The final model for diligence included trajectories that were low and increasing (9.96%), high and decreasing (4.35%), high and relatively consistent (52.17%), and moderate and increasing (33.51%) (see Table 21 and Figure 9). The final model for future mindedness included trajectories that were moderate and increasing

(45.01%), high and relatively consistent (36.12%), high and decreasing (3.45%), and low and increasing (15.43%) (see Table 25 and Figure 10). The final model for purpose included trajectories that were high and decreasing more steeply (12.20%), low and relatively consistent (5.46%), moderate and increasing (24.95%), low and increasing (0.91%), high and decreasing (32.24%), and high and increasing (24.23%) (see Table 29 and Figure 11).

The next steps for this dissertation were to consider patterns of class membership between models and to determine if ISR and prosocial socialization predicted convergence in high levels of character attributes. However, based on final models within each character attribute, there were a total of 3,456 possible class patterns between all character attributes. Due to the number of participants, there was not sufficient information to estimate a multiway frequency table which would have provided estimates for whether there were significantly prevalent class patterns. There was also not enough information to estimate chi-square tests to determine significant patterns in pairwise comparisons of class membership. Both analyses were attempted, and there were multiple cells with less than five predicted cases, which indicated that model estimates would not be reliable (Field, 2013). Accordingly, class patterns were considered descriptively.

There were 264 observed class patterns, with the modal pattern occurring 29 times (5% of the sample). This modal pattern involved membership in the following classes: high and decreasing honesty, humility, and purpose and high and relatively consistent diligence and future mindedness. This class pattern could be considered "Machiavellian" based on the decreases in moral-based character attributes with the consistent drive toward goals. However, end point class estimates for honesty, humility, and purpose remained high, which provided evidence for high levels of these character attributes even with decreases.

Beyond the modal pattern, there was one pattern with 23 participants, one pattern with 12 participants, two patterns with ten participants, 84 patterns with between two and nine participants, and 175 unique class patterns. To consider relations between character attribute trajectories, predicted start, middle, and end points were estimated for each participant based on class-level estimates for intercept (i.e., start point) and slope (i.e., the amount of deviation at each time point). Specifically, the class-estimated intercepts were used as the predicted start points. The class-estimated slopes were added to the start points to calculate the class-estimated middle point. Class-estimated slopes were added to the class-estimated middle points to calculate the class-estimated end points. Correlations of class-level estimated character attributes at each time point were calculated and every bivariate correlation was positive and statistically significant, which provided evidence that all character attributes were positively associated with one another within and between time points (see Table 30).

ISR and Prosocial Socialization as Predictors of Trajectories

The large number of observed class patterns and the significantly larger possibilities of class patterns based on the final growth mixture models led to a need for alternative considerations of the relations of ISR and prosocial socialization to the trajectories of character attributes to address research question 3. As such, two types of analyses were conducted. First, multinomial logistic regressions were conducted for each character attribute in Mplus Version 7.4 to consider the associations between ISR and prosocial socialization with the trajectories within each final character attribute model. Second, categories of class patterns were created using the class-predicted start, middle, and endpoints described above and binary logistic regressions were conducted using SPSS version 24.0 to determine if ISR and prosocial socialization predicted these class pattern categories.

Latent class multinomial logistic regressions. Multinomial logistic regressions were conducted using the automatic 3-step method incorporated into Mplus 7.4 software to consider the associations between ISR and prosocial socialization with the final models for each character attribute separately (Asparouhov & Muthén, 2014). Specifically, class membership for each attribute was regressed on ISR and prosocial socialization. The automatic 3-step method fixed class proportions such that inclusion of the predictors did not result in individuals shifting class membership. Using the automatic 3-step method ensured that the estimates of the effects of the predictors were limited to estimating the association of each predictor on class membership, without having an effect on the class membership itself. Multinomial logistic regressions were estimated with rotating reference classes for each character attribute. Based on a priori assumptions that gender would be associated with class membership, class membership was also regressed on "girl." However, identifying as a girl was only a significant predictor of class membership in one of the 45 comparisons estimated. As such, gender was dropped from the final regression models. Results are reviewed for each character attribute separately. I used an alpha level of .05 to determine significance of analyses. Bonferroni corrections were employed to correct for the number of comparisons conducted simultaneously. Given that many researchers consider Bonferroni corrections to be overly conservative (e.g., Perneger, 1998), results are presented with and without these corrections.

Honesty. Estimates are included in Tables 31 through 36.

Intentional self-regulation. ISR predicted class membership in nine of 30 comparisons. Participants with higher ISR were significantly less likely to be in the class characterized by low and increasing honesty than the classes characterized by high and relatively consistent honesty, high and decreasing honesty, moderate and increasing honesty, and high honesty that was decreasing more steeply (see Table 36). Participants with higher ISR were also significantly more likely to be the class characterized by high and decreasing honesty compared to the classes characterized by high and relatively consistent or moderate and relatively consistent honesty (see Tables 31 and 35). Finally, participants with higher ISR were significantly more likely to be in classes characterized by high and consistent, moderate and increasing, and high and decreasing levels of honesty compared to the class characterized by moderate and relatively consistent levels of honesty (see Table 35).

Several of these significant comparisons were not maintained given Bonferroni corrections, which required a *p*-value less than .002. Given Bonferroni corrections, participants with a one-unit higher score on ISR were about three times more likely to be in the class characterized by high and relatively consistent honesty and about five times more likely to be in the class characterized by high and decreasing honesty than the class characterized by low and increasing honesty (see Table 36).

Prosocial socialization. Prosocial socialization predicted class membership for three of 30 comparisons. Specifically, participants with higher prosocial socialization were significantly less likely to be in the class characterized by moderate and increasing honesty than the classes that were characterized by high and relatively consistent, high and decreasing, or low and increasing honesty (see Table 32). However, none of these significant comparisons were maintained given Bonferroni corrections.

Humility. Estimates are included in Tables 37 through 42.

Intentional self-regulation. ISR predicted class membership in 12 of 30 comparisons. Participants with higher ISR were significantly more likely to be in the classes characterized by high and decreasing, high and steeply decreasing, and low and relatively consistent humility over the classes characterized by moderate and increasing, low and increasing, and moderate and relatively consistent humility (see Tables 38, 40, and 42). Additionally, participants with higher ISR were significantly more likely to be in the class characterized by moderate and increasing humility over the classes characterized by low and increasing and moderate and relatively consistent humility (see Tables 40 and 42). Finally, participants with higher ISR are more likely to be in the class characterized by moderate and relatively consistent humility over the class characterized by low and increasing humility (see Table 40).

Several of these significant comparisons did not remain after conducting Bonferroni corrections, which required a *p*-value less than .002. Given Bonferroni corrections, participants with a one-unit higher score on ISR were about 6.5 times more likely to be in the class characterized by high and decreasing humility than the class characterized by moderate and increasing humility and about 68 times more likely to be in the class characterized by high and decreasing humility than the class characterized by low and increasing humility (see Tables 38 and 40). Participants with a one-unit higher score on ISR were also about 10 times more likely to be in the class characterized by moderate and increasing humility than the class characterized by low and increasing humility (see Table 40); about 42 times more likely to be in the class characterized by high humility that was decreasing more steeply than the class characterized by low and increasing humility (see

Table 40); about 20 times more likely to be in the class characterized by high and decreasing humility compared to the class characterized by moderate and relatively consistent humility (see Table 42); about three times more likely to be in the class characterized by moderate and increasing humility compared to the class with moderate and relatively consistent humility (see Table 42); and about 13 times more likely to be in the class characterized by high humility that was decreasing more steeply compared to the class characterized by moderate and relatively consistent humility (see Table 42).

Taken together, participants with higher ISR score were much more likely to be in a class characterized by high start points for humility over low and moderate start points, even in cases where classes characterized by high levels of humility at start points had trajectories that decreased significantly. Higher ISR was associated with classes characterized by moderate levels of humility over low levels of humility only when trajectories both demonstrated a significant increase. Higher ISR was associated with classes characterized by moderate levels of humility that increased over classes characterized by moderate levels of humility that stayed relatively consistent.

Prosocial socialization. Prosocial socialization predicted class membership in two of 30 comparisons. Participants with higher prosocial socialization were significantly more likely to be in the class characterized by high and decreasing humility than the class characterized by low and increasing or moderate and relatively consistent humility (see Tables 40 and 42). However, these significant comparisons were not maintained given Bonferroni corrections.

Diligence. Estimates are included in Tables 43 through 46.

Intentional self-regulation. ISR predicted class membership in five of 12 comparisons. Specifically, participants with higher ISR were significantly more likely to be in the classes characterized by high and decreasing and high and relatively consistent diligence than the classes characterized by low and increasing and moderate and increasing diligence (see Tables 43 and 46). Additionally, participants with higher ISR were more likely to be in the class characterized by moderate and increasing diligence than the class characterized by low and increasing diligence (see Table 43).

Four of these comparisons were maintained given Bonferroni corrections, which required a *p*-value less than .004. Specifically, participants with a one-unit higher score on ISR were about 650 times more likely to be in the class characterized by high and decreasing diligence; about 980 times more likely to be in the class characterized by high and relatively consistent diligence; and about 50 times more likely to be in the class characterized by moderate and increasing diligence all compared to the class characterized by low and increasing diligence (see Table 43). Additionally, participants with a one-unit higher score on ISR were about 20 times more likely to be in the class characterized by high and relatively consistent diligence compared to the class characterized by moderate and increasing diligence (see Table 46).

Prosocial socialization. Prosocial socialization predicted class membership in two of 12 comparisons. Participants with higher prosocial socialization were significantly more likely to be in the classes characterized by low and increasing diligence than the classes characterized by high and decreasing or moderate and increasing diligence (see Tables 44 and 46). However, these significant associations were not maintained given Bonferroni corrections.

Future mindedness. Estimates are included in Tables 47 through 50.

Intentional self-regulation. ISR predicted class membership in five of 12 comparisons. Specifically, participants with higher ISR were significantly more likely to be in the classes characterized by high and relatively consistent and high and decreasing future mindedness than in the classes characterized by moderate and increasing and low and increasing future mindedness (See Tables 47 and 50). Additionally, participants were significantly more likely to be in the class characterized by moderate and increasing future mindedness than the class characterized by low and increasing future mindedness (see Table 50).

All of these comparisons were maintained given Bonferroni corrections, which required a *p*-value less than .004. Participants with a one-unit higher score on ISR were about eight times more likely to be class characterized by high and relatively consistent future mindedness and about 18 times more likely to be in the class characterized by high and decreasing future mindedness compared to the class characterized by moderate and increasing future mindedness (see Table 47). Participants with a one-unit higher score on ISR were about six times more likely to be in a class characterized by moderate and increasing future mindedness; about 50 times more likely to be in a class characterized by high and relatively consistent future mindedness; and about 114 times more likely to be in a class characterized by high and decreasing future mindedness compared to a class characterized by low and increasing future mindedness (see Table 50).

Prosocial socialization. Prosocial socialization predicted class membership in two of 12 comparisons. Participants with higher prosocial socialization were significantly more likely to be in the class characterized by high and relatively consistent future mindedness than the classes characterized by moderate and increasing or low and increasing future mindedness (see Tables 47 and 50). However, these significant associations were not maintained given Bonferroni corrections.

Purpose. Estimates are included in Tables 51 through 56.

Intentional self-regulation. ISR predicted class membership in 11 of 30 comparisons. Participants with higher ISR were significantly more likely to be in the classes characterized by high purpose that was decreasing more steeply and high and decreasing purpose than the classes characterized by low and relatively consistent, moderate and increasing, and low and increasing purpose (see Tables 52-54).

Participants with higher ISR were significantly more likely to be the class characterized by moderate and increasing and the high and increasing purpose than the classes characterized by low and relatively consistent and low and increasing purpose (see Tables 52 and 54). Finally, participants with higher ISR were more likely to be in the class characterized by high and decreasing purpose than the class characterized by high and increasing purpose (see Table 56).

Several of these comparisons were maintained given Bonferroni corrections, which required a *p*-value less than .002. Participants with a one-unit higher score on ISR were about four times more likely to be in the class characterized by high purpose that was decreasing more steeply; about eight times more likely to be in the class characterized by high and decreasing purpose; and about three times more likely to be in the class characterized by high and increasing purpose compared to the class characterized by low and relatively consistent purpose (see Table 52). Participants with a one-unit higher score on ISR were about four times more likely to be in the class characterized by high and decreasing purpose compared to the class characterized by moderate and increasing purpose (see Table 53). Additionally, participants with a one-unit higher score on ISR were about 14 times more likely to be in the class characterized by high and decreasing purpose compared to the class characterized by low and increasing purpose (see Table 54).

Prosocial socialization. Prosocial socialization predicted class membership in eight of 30 comparisons. Participants with higher prosocial socialization were significantly more likely to be in classes characterized by low and increasing or high and decreasing purpose than the classes characterized by purpose that was high and decreasing more steeply, low and relatively consistent, or moderate and increasing (see Tables 51-53). Participants with higher prosocial socialization were also significantly less likely to be in classes characterized by low and relatively consistent purpose than the classes characterized by moderate and increasing or high and increasing purpose (see Tables 53 and 56).

Three of these significant comparisons were maintained given Bonferroni corrections, which required a *p*-value less than .002. Participants with a one-unit higher score in prosocial socialization were about four times more likely to be in classes characterized by low and increasing and high and decreasing purpose compared to the class characterized by low and relatively consistent purpose (see Table 52). Participants with a one-unit higher score in prosocial socialization were about 2.5 times more likely to be in the class characterized by high and decreasing purpose compared to the class characterized by moderate and increasing purpose (see Table 53).

Binary Logistic Regressions of Class Membership. To investigate the associations between ISR and prosocial socialization on overall class patterns, class-level predicted start, middle and end points, described above, were dichotomized into greater than or equal to three and below three for each character attribute at each measurement occasion. Three was used as the cut-off point because this was the mid-point of the scale for each attribute. Although using cut-off points was not ideal, the complexity of possible trajectory patterns and the limited sample size meant that using cut-off to inform dichotomizing of trajectory patterns was one of the few ways in which to consider associations between contextual factors and patterns of character attribute trajectories.

In the data, it was not common for classes to have predicted scores of less than three for start and end points in any trajectory within any character attribute. Specifically, about 6% of the sample had predicted honesty values that started below three which decreased to 1% of the sample having predicted honesty values that ended below three. Seven percent of the sample had predicted humility values that started above three which decreased to 4% of the sample having predicted humility values that ended above three. Ten percent of the sample had predicted diligence values that started above three and 4% of the sample had predicted diligence values that ended below three. Fifteen percent of the sample had predicted future mindedness values that started above three and 19% of the sample had predicted future mindedness values that ended below three. Finally, 6% of the sample had predicted purpose values that started and ended below three. There were no individuals for whom all five character attributes were predicted to end lower than three. The low prevalence of low levels of these character attributes had implications for the interpretation of logistic regression results which are reviewed in the Discussion.

There were four possible patterns of character attribute trajectories, defined as *increasing*, *decreasing*, *consistently mixed*, or *consistently high*. A class pattern was classified as increasing if it had low (i.e., less than three) class-level predicted start points for all character attributes and high (i.e., greater than three) class-level predicted end points for one or more of these character attributes. A class pattern was also classified as increasing if class-level predicted start points for character attributes were mixed (i.e., some less than three and some greater than three) and class-level predicted end points were all high (i.e., greater than three). For example, a person would be in this category if they started low on all five character attributes and ended low on honesty and humility but high in diligence, future mindedness, and purpose. A person would also be in this category if they started low on honesty and humility and high on diligence, future mindedness, and purpose and ended high on all five character attributes. Within this class pattern, observed individual character attribute patterns included increasing or maintaining high honesty, humility, and diligence, and having consistently low or consistently high future mindedness and purpose.

A class pattern was classified as decreasing if all five character attributes were predicted to have high start points and some of these five were predicted to have low end points. For example, an individual would be in this classification if they started with all five character attributes predicted to be high but ended with low predicted levels of honesty and humility. As noted above, there were no individuals for whom all five character attributes were predicted to end lower than three. Within this class pattern, observed character attribute patterns included decreasing or consistently high honesty, humility, diligence, and future mindedness and consistently high purpose.

A class pattern was classified as consistently mixed if there were consistently some character attributes that were predicted to be low and some that were predicted to be high. For example, a person would be this category if they were predicted to start with high levels of honesty and humility and low levels of diligence, purpose, and future mindedness and they were predicted to end with high levels of humility and diligence and low levels of honesty, future mindedness, and purpose. There were many observed class patterns within this classification. Honesty was observed to be increasing or consistently high. Humility was observed to be increasing, decreasing, consistently low, or consistently high. Diligence was observed to be increasing, decreasing, or consistently high. Future mindedness was observed to be decreasing, consistently low, or consistently high. Purpose was observed to be consistently low or consistently high. Individuals missing on future mindedness or purpose were included in this classification.

A class pattern was classified as consistently high if predicted estimates for all five character attributes were high across all time points. The frequencies of the class patterns were as follows: 44 participants were classified as increasing with mixed to high class patterns (n = 42) or low to mixed class patterns (n = 2); 37 participants were classified as decreasing from high to mixed class patterns, 109 participants had consistently mixed class patterns, and 362 participants had consistently high class patterns.

A multinomial logistic regression was attempted for these four outcomes using SPSS version 24.0 but the model was unable to be estimated. It is possible that the assumption of independence of possible outcomes was violated by the data. Specifically, estimating multinomial logistic regressions involves estimating a set of binary logistic regressions, and this is only possible if the comparisons between each set are not affected by the presence of another possibility. For example, a multinomial logistic regression could not be conducted if the likelihood of whether someone would be in the increasing or decreasing class pattern was affected by the possibility of being in the consistently mixed class pattern. Due to this analysis not being possible, binary logistic regressions were estimated for each possible pattern of class memberships. These analyses did not share the constraint of this assumption because the only possible outcomes for each analysis were the individual being in or not being in the classification.

Four binary logistic regressions with the outcomes of increasing class pattern, decreasing class pattern, consistently mixed class pattern, and consistently high class pattern. ISR and prosocial socialization were included as predictors in all four binary logistic regressions. To correct for multiple comparisons, Bonferroni corrections were employed on the set alpha level of .05. The corrected *p*-value to identify significant comparisons was $< .025$. Although Bonferroni corrections are sometimes considered overly restrictive, significant results in these analyses all met the standards of these corrections. A summary of binary logistic regression findings can be seen in Tables 57 through 60.

Classification in the increasing class pattern was negatively predicted by higher levels of ISR. Specifically, a participant with a one-unit higher score in ISR was about 2.5 times less likely to be classified in the increasing class pattern compared to not classified in the increasing class pattern (see Table 57).

Classification in the decreasing class pattern was positively predicted by higher levels of ISR. Specifically, a participant with a one-unit higher score in ISR was about 2.5 times more likely to be classified in the decreasing class pattern compared to not classified in the decreasing class pattern (see Table 58).

Classification in the consistently mixed pattern was negatively predicted by higher levels of ISR. Specifically, a participant with a one-unit higher score in ISR was about 4 times less likely to be classified in the consistently mixed class pattern compared to not classified in the consistently mixed class pattern (see Table 59).

Classification in the consistently high class pattern was positively predicted by higher levels of ISR. Specifically, a participant with a one-unit higher score in ISR was about 3 times more likely to be classified in the consistently high class pattern compared to not classified in the consistently high class pattern (see Table 60).

Prosocial socialization did not significantly predict classification in any of the four class patterns.

Discussion

In this dissertation, I aimed to contribute to the understanding of adolescent character development from an RDS perspective. I completed analyses focused around five character attributes and two contextual variables in data collected from adolescents in New England over a two year period. The character attributes considered were honesty, humility, diligence, future mindedness, and purpose and the contextual variables considered were ISR and prosocial socialization from a known role model. A summary of findings can be found in Table 61.

Trajectories of Character Attributes

Based in RDS principles of plasticity and interindividual differences, I expected that levels of character attributes would change within individuals and that trajectories would differ between individuals. Using growth mixture modeling, I identified trajectories and groups of trajectories within each character attribute. All sets of trajectories selected were within an LCGA specification, meaning that intercept and slope estimates varied between trajectory classes but not within trajectory classes. Based on consideration of multiple fit statistics and classification diagnostics, six-class models were selected for honesty, humility, and purpose and four-class models were selected for diligence and future mindedness.

Considerations of classes within these models provides evidence for patterns of increasing, stable, and decreasing levels of each character attribute, with high, middle, and low initial levels for all attributes. These findings support the RDS principles of plasticity and individual differences from which this research question was derived (Lerner, 2018). These findings are in contrast to the work of Peterson and Seligman (2004) who considered each of these character attributes to be traitlike (i.e., largely immutable to contextual factors). In most cases (65.58%), participants had sustained and high levels of all character attributes. However, there were participants for whom changes in their character attributes were substantial. For example, there were about eight participants estimated to be in a class characterized by honesty that started at about 5 and ended at about 2.2, going from "I tell the truth" being *Just like me* to *A little like me.* Additionally, there were about 18 participants estimated to be in a class characterized by humility that started at about 4.67 and ended at about 2.61, going from *A lot like me* to *A little like me*. The fact that these trajectories are possible means that it is not sufficient to measure character attributes at one point and consider them immutable to change. This is good news for character education efforts aimed at increasing character attributes in adolescence.

Comparison of Character Attribute Trajectories

The number of possible trajectories within each character attribute in combination with the number of participants in this sample led to an issue stemming from a lack of information in estimating patterns of character attribute trajectories. Specifically, there were 3,456 possible patterns and it was not possible to estimate patterns of character attribute trajectories using a multi-way frequency table or chi-square analyses because so few class patterns were represented (given the small size of the sample relative to the number of possible patterns). Instead, class patterns were considered descriptively, and most patterns were unique to individual participants. Thus, instead of patterns of class membership, comparisons were conducted by examining bivariate correlations of levels of each character attribute at each time point.

Class-level estimates of intercept and slope were used to calculate predicted start, middle, and end points for each individual and these values were correlated for the overall sample. Results of this analysis supported the second research question by providing evidence that all character attributes were positively and significantly correlated within and between time points. These significant associations support past theoretical and empirical findings of associations between character attributes (e.g., Bronk, 2008; Castro Solano & Consentino, 2016; Fowers & Davidov, 2006; Han, 2015; Hill et al., 2016; Linver & Urban, 2018; Stoddard & Pierce, 2015; Strobel et al., 2013). This finding also extended the character literature by providing empirical evidence for associations for a larger subset of character attributes, whereas most literature reviewed has considered only two attributes at a time. Finding associations between multiple character attributes simultaneously supports movement toward an empirical understanding of character as a multi-faceted system (e.g., Park, 2014).

ISR and Prosocial Socialization as Predictors of Trajectories

Finally, in this dissertation I considered the associations between character attribute trajectories and contextual factors of ISR and prosocial socialization by known role models. Gender was initially included as a covariate based on previous literature indicating that girls tend to have higher levels of character attributes in some cases (Carlo et al., 2007; Hoffman, 1979; Ottoni-Wilhelm et al., 2014; Peterson & Seligman, 2004), but was removed from analyses due to a lack of associations with most outcomes. This may have been the case for these analyses because of the limited variation in levels of each character attribute overall. This also may have been the case due to other factors which may have influenced similar perspectives from male and female participants, such as generally high levels of socioeconomic status across most participants and the fact that most of the in-school sample participants came from parochial schools, which may have promoted character attributes as central to their Christian mission.

Associations between character attribute trajectories and contextual factors were considered within each character attribute trajectory model and for patterns of character attribute trajectory membership. Associations between each character attribute trajectory model and ISR and prosocial socialization were considered using multinomial logistic regression analyses. Overall class patterns were simplified into increasing, decreasing, consistently mixed, and consistently high by examining patterns of class-level predicted estimates at start and end points. Using cut-off scores and dichotomizing the outcomes was necessary to provide enough information for binary logistic regression estimates of these class patterns on ISR and prosocial socialization. In both sets of regressions, ISR significantly predicted high start points for each character attribute and for overall character attribute patterns.

Within honesty, humility, future mindedness, and purpose higher scores on ISR were associated with a higher likelihood of membership in the classes characterized by higher start points for each attribute, even in cases where classes characterized by high start points had slopes that decreased significantly and when classes were characterized by low start points and significantly increased. Within diligence, higher scores on ISR were also associated with a higher likelihood of membership in classes characterized by higher start points.

Classes characterized by low and increasing character attributes had a predicted start point for each attribute of below three, whereas the classes characterized by moderate or high character attributes by definition had start points for character attributes that were greater than or equal to three. This is important to note because the significant associations established between ISR and character attribute trajectories suggest that ISR had concurrent associations with high levels of character attributes that were not sustained, given that ISR in these analyses was measured only at Wave 2. For example, participants with higher ISR were significantly more likely to be in classes characterized by high and relatively consistent or high and decreasing honesty compared to participants in the class characterized by low and increasing honesty. Participants with higher ISR were much more likely to be in classes characterized by higher start points for all character attributes. When considering associations between ISR and purpose trajectories, participants with higher ISR were even more likely to be in the class characterized by high and decreasing purpose compared to the class with high and relatively consistent purpose. In this case, the initial level of purpose was higher in the class characterized by high and decreasing purpose, further reinforcing the idea that ISR was concurrently associated with higher levels of character attributes. Alternatively, it may be that ISR itself was decreasing in conjunction with decreasing character attributes. Whether ISR was decreasing could not be assessed in these analyses because I used time-invariant predictors.

In character attribute trajectory patterns, ISR was found to negatively predict increasing levels of character attributes and to positively predict decreasing levels of character attributes. This finding may seem to be counterintuitive to the theoretical benefits of ISR and its associations with thriving (e.g., Gestsdóttir et al., 2009), but it is in line with the multinomial logistic regression findings as it reinforces that ISR was significantly associated with character attributes at higher start points. ISR was found to negatively predict consistently mixed attributes and to positively predict consistently high attributes. This further reinforces the idea that ISR was concurrently associated with high levels of character attributes. It is also possible that ISR may have decreased similar to decreasing patterns of character attributes. As noted above, whether ISR was decreasing could not be assessed in these analyses because I used time-invariant predictors.

Prosocial socialization was not significantly associated with character attribute trajectories for honesty, humility, diligence, or future mindedness. Within purpose, higher scores on prosocial socialization were associated with a higher likelihood of membership in classes characterized by low and increasing and high and decreasing purpose over the class characterized by low and relatively consistent purpose. Additionally, higher scores on prosocial socialization were associated with a higher likelihood of membership in the class characterized by high and decreasing purpose compared to the class characterized by moderate and increasing purpose. These associations do not appear to have a clear pattern. This could be evidence that prosocial socialization had a different impact on different participants. For example, those in the class characterized by high and decreasing purpose could be individuals for whom prosocial socialization was not being recognized or *sticking* as well as it was for participants in the class characterized by low and increasing purpose. Indeed, it may not be realistic to expect sustained effects of socialization given that I do not know if experienced socialization changed for participants because this predictor was time-invariant.

Prosocial socialization did not significantly predict membership in any overall character attribute patterns. This was in contrast to expectations that prosocial socialization would be associated with youth character, as close relationships with caring and committed adults were associated with positive outcomes for youth in the PYD literature (e.g., Theokas & Lerner, 2006). Interestingly, findings provide evidence more in line with Napolitano et al. (2011), who found that close relationships with parents were not necessary for one aspect of thriving, operationalized as goal optimization. Although goal optimization is a part of ISR, the findings of Napolitano et al. (2011) are similar to the findings of this dissertation in that there were unexpected individual differences in the association between adult support and optimal youth outcomes, in this case operationalized as high and consistent or increasing levels of character attributes.

These findings did not support my hypotheses that ISR and prosocial socialization would be associated with optimal character attribute trajectories. Instead, they provided evidence that high levels of ISR and prosocial socialization at one time point are not enough to support sustained and high levels of character attributes. It is possible that these analyses were impacted by the ways in which the character attributes and contextual variables were measured and the analyses chosen. Limitations and suggestions for future research are reviewed below.

Implications

As noted above, this dissertation provided evidence for trajectories of character attributes as well as correlations between character attributes. There is evidence for different associations between ISR and prosocial socialization with trajectories of character attributes. ISR is associated with higher start points but does not appear to have a sustained positive relation with character attributes. Prosocial socialization presents as having different associations with trajectories for purpose that do not have a clear pattern. An association between prosocial socialization and character attribute trajectories was expected given past associations between positive socialization and prosocial outcomes in youth (e.g., Carlo et al., 2007). It is possible that the narrow measure socialization considered in this dissertation along with the lack of consideration of the youth-role model relationship quality could have contributed to the findings in this area. The associations that were significant provided evidence that prosocial socialization may not stick in the same way for all individuals and that ISR may not have a sustained positive association with character attributes. However, given that ISR and prosocial socialization were time-invariant predictors, it is also possible that each did have a sustained effect that was not captured due to their trajectories not being considered in these analyses.

These findings provided evidence that experiencing early ISR and prosocial socialization may not be enough to promote high and sustained levels of character. It may be that there is more needed in a role modeling relationship than modeling good character, such as high-quality relationships typified by emotional closeness and support. Further, it may be that ISR and prosocial socialization themselves are changing. Youth may need additional supports to promote their maintenance and increase the positive effects of each.

Limitations and Future Directions

As noted in the overview of participants, the sample included in these analyses was limited in racial and socioeconomic diversity. As such, the results of these analyses should not be generalized beyond the scope of the sample details above, which was largely White with college-educated and employed parents, living in the Northeast U.S. Future studies could consider these findings in a broader, more diverse sample of individuals or whether these findings hold in a similar sample. In doing so, evidence could be established for the importance of these character attributes in adolescence as well as these and additional contextual factors that can promote these attributes.

This dissertation was limited by the ways in which variables were measured in the CABB study. Specifically, this dissertation was limited by how honesty and purpose were measured.

Honesty was measured using only one item. This was not ideal for empirical reasons as the scores for the variable could only range from one to five, in contrast to other scale scores which could potentially be any value between and inclusive of 1 and 5. Although previous researchers have allowed for variables with only five options to be considered *continuous*, technically these response options were limited to five categorical options. In addition to empirical considerations, having one item limited the connections that could be made between honesty in this dissertation and previous literature. Specifically, the CABB study only included the item "I tell the truth." There was no consideration of contextual factors considered in previous studies, such as why individuals may be motivated to tell the truth or not in particular contexts, considered by Hartshorne and May (1928). Further, honesty could not be necessarily interpreted as representing authenticity, as posited by Peterson and Seligman (2004) or as being directly connected to humility, as posited by the HEXACO model (e.g., Ceschi et al., 2016). Therefore, although this dissertation does support that honesty may change and that there may be interindividual differences in this change, the findings are difficult to connect to the previous literature based on the limited scope of honesty's measurement. This limitation can be addressed in future studied by operationalizing honesty using more than one item in an attempt to fully capture this construct as it has been defined in the literature.

Purpose was measured by considering the importance of different life goals, some that were theoretically self-oriented and some that were theoretically other-oriented. These life goals were presumed to make up the intention aspect of Damon et al.'s (2003) definition of purpose as "a stable and generalized intention to accomplish something that is at once meaningful to the self and of consequence to the world beyond the self" (p. 121). Simply measuring the importance of life goals does not ensure that individuals are working toward these goals, but the idea of purpose as guiding other youth character attribute was central to the reason this construct was included in these analyses. Future studies considering this or a similar subset of character attributes should consider other questions about purpose, such as whether individuals are actually working toward their purposeful goals, which was implicitly assumed in this dissertation. Preliminary analyses on purpose revealed that there were empirical weaknesses in this construct. Specifically, when using confirmatory factor analyses to choose items for purpose, the final model chosen did not have strong fit criteria for all indexes considered. Additionally, this model did not meet the criteria for weak invariance between groups at Wave 4 or longitudinally. Finally, the final trajectory model chosen for purpose was the most similar in terms of fit criteria and classification diagnostics considered to the alternate candidate model that was not chosen. These empirical difficulties suggest that purpose may be the construct with the weakest construct validity in the sample, providing evidence that results should be taken with caution. Future studies may wish to consider purpose in a similar way to the other character attributes measured in the CABB study – by asking youth about their perspective on their purpose more directly rather than inferring their purpose based on the importance they assign to life goals.

In this dissertation, I was limited in the ability to compare trajectories between character attributes. Specifically, the number of possible trajectories and the sample size led to a lack of information necessary to appropriately estimate chi-square analyses or a multi-way frequency table, which would have allowed me to consider statistically significant associations between all possible character attribute trajectories. Instead, patterns were considered descriptively and class-estimated start, middle, and end points were correlated to determine that character attributes were significantly and positively associated.

Overall class patterns were simplified into four categories to allow for regression of class patterns on ISR and prosocial socialization. These four categories were created by taking the class-estimated start, middle, and end points and dichotomizing them as high or low. Patterns of high and low estimations were considered between time points and between character attributes to classify individuals into patterns of increasing, decreasing, consistently mixed, or consistently high character attribute patterns. Using cut-off points is certainly not ideal in research as the findings from the subsequent logistic regression analyses were limited to predicting these four outcomes, characterized by patterns of high or low attributes over time, rather than the associations between the full range of possible character attribute trajectory memberships. Given the number of possible class patterns based on these analyses, future studies should aim for larger numbers of participants so as to be able to consider associations of more complex trajectory patterns and contextual factors.

It was important to interpret outcomes of these class pattern analyses carefully, as at first glance it appeared that ISR was associated with decreasing character attributes overall. However, based on the cut-off points and consideration of results within multinomial logistic regression models, it was more likely that ISR was concurrently associated with high levels of character attributes. Concurrent associations between ISR and high levels of character attributes would explain associations with the decreasing pattern as decreasing patterns had to start at high levels by definition.

In addition to the limited possible outcomes, using cut-off points is not ideal because the chosen cut-off points are largely arbitrary. If response patterns were more normally distributed it may have made sense to choose three as a cut-off point. However, observed data demonstrated a skew toward higher levels of all character attributes. Three was chosen as the line between high and low levels of a character attribute in an attempt to create an objective point at which character changes from low to high – the middle point of each scale. However, in this sample, as noted above, there were few participants below this middle point on any character attribute at the start or end points. Perhaps individuals who were below four in this sample would actually be individuals with low character, given the skewed distributions. Future analyses should consider whether this positive skew exists in a larger sample and perhaps work to standardize the outcomes such that the mean is zero for ease of analysis. However, ideally, future analyses would have a large enough sample so as to not require the use of cut-off points.

These analyses were also limited in that predictors were considered to be time-invariant. Specifically, estimates for ISR and prosocial socialization were taken from the first measurement occasion. Results provided evidence that high levels of ISR predicted high start points of all character attributes, but not necessarily sustained high levels of each character attribute. It may be beneficial in future analyses to consider ISR as a time-varying predictor of character-related outcomes to allow researchers to consider whether a lack of sustained high character attributes may actually be related to decreases in ISR. Considerations of prosocial socialization as a time-varying predictor would allow researchers to consider how changes in the youth-role model relationship may be associated with changes in character, perhaps providing a clearer explanation for the varied associations found in these analyses. In addition to considering prosocial socialization as a time-varying predictor, future studies may want to consider other aspects of the youth-role model relationship that may promote the positive effects of prosocial modeling. For example, prosocial socialization will likely be a more effective practice if the youth feels close to and trusts their role model. Thus, it would be important to measure emotional closeness in addition to prosocial socialization practices. Qualitative interviews of youth engaging in prosocial behaviors and identifying as having high levels of character attributes could provide additional insight into how role models may effectively support these outcomes. Future studies may also want to consider who the role model is (e.g., parent, teacher) and the qualities of the relationship between the youth and their role model (e.g., level of emotional closeness or support). It is important to consider these additional aspects of the role modeling relationship because the results of these analyses provide evidence that high levels of ISR and prosocial socialization at one time point are not enough for sustained and high levels of character attributes.

Beyond expanding the constructs directly related to those currently considered, additional demographic predictors may be helpful to provide a further understanding of the current results as well as future research on character development. For example, it would likely be helpful to include age as a predictor of the character attribute trajectories. It is possible that character development is a natural part of development, and that increases in identification with character attributes would occur over time. Increases in certain character attributes could be associated with cognitive development, maturity, and development of peer relationships. For example, higher levels of humility are associated with empathy and perspective taking, both of which could develop as part of more mature, caring peer relationships. Further, higher levels of future mindedness are likely associated with cognitive development as a person needs to be able to conceive of the future to be able to think about and plan for it. Given these potential interconnections, age will be an important contextual factor to consider in future research. This would be important to examine in a sample with a wider range of ages, and over a longer period of time than that covered by the present dissertation.

These analyses were also limited in the outcomes considered. The character attributes included are important characteristics to consider, due to their prevalence in the character education literature and their theoretical and empirical associations with positive outcomes. However, they do not represent the full scope of possible positive outcomes for youth or the full set of indicators for youth thriving. Future studies may want to consider alternate indicators of youth thriving, such as positive youth development in terms of the 5 Cs (Lerner et al., 2015) or additional character attributes, like moral courage or empathy.

In this dissertation, I assumed that high levels of character attributes were important because they would be tied to youth prosocial behaviors, such as setting and achieving other-oriented goals. However, I did not consider youth contribution as a potential distal outcome of high levels of character. This was in part because, while the CABB study did include items related to prosocial actions, the variance on these measures was low. Specifically, youth were asked how often they engaged in prosocial actions like helping others they knew or did not know, approximately 90% of youth reported that they engaged in these activities. There were strong theoretical reasons to believe that having high levels of character attributes would be tied to youth thriving and contribution. However, future studies should consider whether there is an empirical tie between high levels of character attributes and contribution as a distal outcome. While it is important to always consider positive outcomes, future research may also want to consider the association between ISR and role models with reduced negative outcomes. PYD researchers have had mixed findings in regard to the association between youth thriving, contribution, and reduced risk behaviors. It is likely that the relationship is more complex than higher levels of character being associated with increased contribution and reduced risk behaviors, but further research is needed to examine these associations.

Conclusion

This dissertation provided evidence that honesty, humility, diligence, future mindedness, and purpose are character attributes that could change within a short period in adolescence. There was evidence that high levels of honesty, diligence, future mindedness, and purpose were associated with ISR, although high levels of ISR alone did not appear to be enough to sustain high levels of these character attributes in all participants. Prosocial socialization by known role models appeared to have different associations with character attribute development for different groups of participants. These findings suggest that there are other aspects of the youth context that may be associated with high levels of character attributes that should be considered in future studies. For example, beyond considering how prosocial socialization alone may promote positive outcomes, researchers should simultaneously consider the quality of the relationship between a youth and their role model. Additional predictors, aspects of character, and distal outcomes, outlined in the limitations above, should also be considered.

Taken together, this dissertation advanced the study of adolescent character development from an RDS perspective by considering a small subset of character attributes in a short period of adolescence, with limited contextual factors. It is my hope that these analyses will support further study that expands the character attributes and contextual factors considered, with the ultimate goal of integrating these findings toward the promotion of character education (e.g., Berkowitz, 2011; Pala, 2011). It is important to address the limitations of this dissertation and to expand the scope of this research, in terms of predictors, character attributes examined, and distal outcomes, so as to connect the narrow area of character development with the broader PYD, RDS, and bioecological models. By considering additional contextual factors, including those outlined above, researchers can continue to build an understanding of the full picture of character development and its contextual supports. This fuller understanding of character development can thereby contribute to optimizing character education and social supports for adolescents. It is my hope that, through this work, the field of adolescent development can continue to grow in its ability to support thriving in adolescence and beyond.

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Tables

Table 1

Character Attribute Items in Analyses

Construct	Prompt	Response options				
	How much are the following statements like you?	Not at all like me	A little like me	Kind of like me	A lot like me	Just like me
Honesty	I tell the truth.					
Humility	It's okay when someone shows me that I made a mistake.					
	I can learn a lot from other people.					
	I can learn from others even if I disagree with them.					
	I am open to changing my ideas.					
Diligence	I finish whatever I begin.					
	I keep working even when something gets hard.					
	I am a hard worker.					
Future mindedness	I think about the consequences of my actions before I do something.					
	I think about all the possible good and bad things that can happen before making a decision.					
	I think about how my decisions will affect others.					

Table 1 (continued)

Construct	Prompt	Response options				
	People may have different types of goals for their lives. Below is a list of goals. How important is each goal to you?	Not Important	Sort of Important	Important	Very Important	Extremely Important
Purpose	Help others					
	Do the right thing					
	Make the world a better place					
	Serve my country					
	Improve my community					

Table 2

Intentional Self-regulation and Prosocial Socialization Items

Construct	Prompt	Response options				
	Below are some statements that may or may not describe you. How much are the following statements like you?	Not at all like me	A little like me	Kind of like me	A lot like me	Just like me
Intentional self-regulation	I always pursue goals one after the other.					
	I think about ways I can best achieve my goals.					
	When things don't work the way they used to, I look for other ways to achieve my goals.					
	When something doesn't work as well as planned, I look at how others achieve that goal.					
	When I decide upon a goal, I stick to it.					
	To attain my goals, I try as many different strategies as I need to.					
	For important goals, I pay attention to whether I need to put in more time or effort.					
	I make every effort to achieve a goal I set.					
	When a goal is important to me, but has little chance of success, I put in extra effort.					

Construct	Prompt	Response options				
	Please answer the following questions about the person you picked.	Never	Rarely	Sometimes	Most of the time	Always
Prosocial Socialization	Does this person encourage you to take part in organizations or activities that promote being a good person?					
	Does this person talk to you about how to be a good person?					
	Does this person encourage you to think about how you would like to be treated in certain situations?					
	Does this person try to understand your point of view when you are talking about moral or ethical issues?					

Table 3

Process of Results

Step	Associated Research Question (RQ)	Purpose
T-Test and Repeated Measures ANOVA	RQ1	Considering differences in honesty between groups and longitudinally
Confirmatory Factor Analyses	RQ1	Confirming the factor structure of character attributes besides honesty
Measurement Invariance – Between-group and Longitudinal	RQ1	Confirming that confirmatory factor analyses hold between groups and longitudinally
Latent Growth Curve Models	RQ1	Considering change in each character attribute in the overall sample
Growth Mixture Modeling	RQ1	Considering subgroups of trajectories within each attribute
Correlations	RQ2	Looking at correlations of class-level predicted attributes at each time point
Multinomial Logistic Regressions by Attribute	RQ3	Considering how intentional self-regulation and prosocial socialization predict character attribute trajectories
Binary Logistic Regressions of Class Patterns	RQ3	Considering how intentional self-regulation and prosocial socialization predict convergence of character attribute trajectories

Note: ANOVA Analysis of variance,

Table 4

Differences in Honesty between Groups

	In-School Sample		Online Sample						
Wave	*M*	*SD*	*M*	*SD*	Condition[a]	*df*	*t*	*p*	Cohen's *d*
Wave 2	3.73	0.88	4.03	0.81	Equal variances assumed	546.00	-4.00	.00	-0.36
Wave 3	3.78	0.87	4.00	0.83	Equal variances not assumed	246.22	-2.51	.01	-0.26
Wave 4	3.84	0.85	4.05	0.84	Equal variances not assumed	254.01	-2.27	.02	-0.25

Note. Groups considered include samples recruited in schools or online.
[a]Condition was determined by examining the results of Levene's Test for Equality of Variances

Table 5

Honesty Repeated Measures ANOVA

	Condition[a]	*df*	Mean square	*F*	*p*	Partial eta squared
Time	Sphericity Assumed	2.00	.22	0.55	.58	< .01
Error(time)	Sphericity Assumed	664.00	.40			

Note: ANOVA Analysis of variance
[a]Condition was determined by examining the results of Mauchly's Test of Sphericity,

Table 6

Model fit From Configural, Loading, and Intercept Measurement Invariance Models for Between-Sample and Longitudinal Invariance Tests for Humility

Model	Type	Chi-square (*df*)	*p*	RMSEA [90% CI]	CFI	TLI	Pass? (Δ CFI ≤ .01)
Wave 2, *N* = 552							
1. Configural	Group	16.19 (8)	.04	0.06 (0.01 to 0.10)	0.98	0.98	
2. Loading	Group	15.62 (7)	.03	0.07 (0.02 to 0.11)	0.98	0.97	Pass (Δ CFI = 0.00)
3. Intercept	Group	18.75 (10)	.04	0.06 (0.01 to 0.10)	0.98	0.98	Pass (Δ CFI = 0.00)
Wave 3, *N* = 454							
1. Configural	Group	26.82 (8)	< .01	0.10 (0.06 to 0.15)	0.96	0.95	
2. Loading	Group	24.03 (7)	< .01	0.10 (0.06 to 0.15)	0.97	0.94	Pass (Δ CFI = 0.00)
3. Intercept	Group	25.33 (10)	< .01	0.08 (0.04 to o.12)	0.97	0.97	Pass (Δ CFI = 0.00)
Wave 4, *N* = 364							
1. Configural	Group	6.05 (8)	.64	0.00 (0.00 to 0.07)	1.00	1.01	
2. Loading	Group	5.36 (7)	.62	0.00 (0.00 to 0.08)	1.00	1.01	Pass (Δ CFI = 0.00)
3. Intercept	Group	5.58 (10)	.85	0.00 (0.00 to 0.05)	1.00	1.02	Pass (Δ CFI = 0.00)
Longitudinal, *N* = 552							
1. Configural	Longitudinal	50.93 (39)	.10	0.02 (0.00 to 0.04)	0.99	0.99	
2. Loading	Longitudinal	55.93 (45)	.13	0.02 (0.00 to 0.04)	0.99	0.99	Pass (Δ CFI = 0.00)
3. Intercept	Longitudinal	63.97 (51)	.10	0.02 (0.00 to 0.04)	0.99	0.99	Pass (Δ CFI = 0.00)

Note: Groups considered include samples recruited in schools or online, *RMSEA* Root Mean Square Error of Approximation, *CFI* Comparative Fit Index, *TLI* Tucker-Lewis Index

Table 7

Model fit From Configural, Loading, and Intercept Measurement Invariance Models for Between-Sample and Longitudinal Invariance Tests for Diligence and Future Mindedness

Model	Type	Chi-square (*df*)	*p*	RMSEA [90% CI]	CFI	TLI	Pass? (Δ CFI ≤ .01)
Wave 2, *N* = 552							
1. Configural	Group	45.75 (22)	< .01	0.06 (0.04 to 0.09)	0.97	0.96	
2. Loading	Group	43.37 (20)	< .01	0.07 (0.04 to 0.09)	0.97	0.96	Pass (Δ CFI = 0.00)
3. Intercept	Group	47.00 (24)	< .01	0.06 (0.03 to 0.08)	0.97	0.97	Pass (Δ CFI = 0.00)
Wave 3, *N* = 454							
1. Configural	Group	48.42 (22)	< .01	0.07 (0.05 to 0.10)	0.97	0.96	
2. Loading	Group	48.30 (20)	< .01	0.08 (0.05 to 0.11)	0.97	0.95	Pass (Δ CFI = 0.00)
3. Intercept	Group	60.84 (24)	< .01	0.08 (0.06 to 0.11)	0.96	0.95	Pass (Δ CFI = 0.01)
Wave 4, *N* = 364							
1. Configural	Group	32.74 (22)	.07	0.05 (0.00 to 0.09)	0.99	0.98	
2. Loading	Group	31.03 (20)	.05	0.06 (0.00 to 0.09)	0.99	0.98	Pass (Δ CFI = 0.00)
3. Intercept	Group	38.22 (24)	.03	0.06 (0.02 to 0.09)	0.98	0.98	Pass (Δ CFI = 0.00)
Longitudinal, *N* =552							
1. Configural	Longitudinal	113.61 (102)	.20	0.01 (0.00 to 0.03)	1.00	0.99	
2. Loading	Longitudinal	138.26 (110)	.04	0.02 (0.01 to 0.03)	0.99	0.99	Pass (Δ CFI = 0.01)
3. Intercept	Longitudinal	148.58 (118)	.03	0.02 (0.01 to 0.03)	0.99	0.99	Pass (Δ CFI = 0.00)

Note: Groups considered include samples recruited in schools or online, *RMSEA* Root Mean Square Error of Approximation, *CFI* Comparative Fit Index, *TLI* Tucker-Lewis Index

Table 8

Model fit From Configural, Loading, and Intercept Measurement Invariance Models for Between-Sample and Longitudinal Invariance Tests for Purpose

Model	Type	Chi-square (*df*)	*p*	RMSEA [90% CI]	CFI	TLI	Pass? (Δ CFI ≤ .01)
Wave 2, *N* = 550							
1. Configural	Group	92.89 (15)	< .01	0.14 (0.11 to 0.17)	0.92	0.90	
2. Loading	Group	92.60 (14)	< .01	0.14 (0.12 to 0.17)	0.92	0.89	Pass (Δ CFI = 0.00)
3. Intercept	Group	94.61 (18)	< .01	0.12 (0.10 to 0.15)	0.92	0.92	Pass (Δ CFI = 0.00)
Wave 3, *N* = 455							
1. Configural	Group	40.14 (15)	< .01	0.09 (0.05 to 0.12)	0.97	0.96	
2. Loading	Group	38.19 (14)	< .01	0.09 (0.06 to 0.12)	0.97	0.96	Pass (Δ CFI = 0.00)
3. Intercept	Group	49.08 (18)	< .01	0.09 (0.06 to 0.12)	0.96	0.96	Pass (Δ CFI = 0.01)
Wave 4, *N* = 366							
1. Configural	Group	62.34 (15)	< .01	0.13 (0.01 to 0.17)	0.93	0.91	
2. Loading	Group	60.59 (14)	< .01	0.14 (0.10 to 0.17)	0.93	0.90	Pass (Δ CFI = 0.00)
3. Intercept	Group	81.80 (18)	< .01	0.14 (0.11 to 0.17)	0.90	0.89	Fail (Δ CFI = 0.03)
Longitudinal, *N* = 552							
1. Configural	Longitudinal	222.51 (72)	< .01	0.06 (0.05 to 0.07)	0.96	0.93	
2. Loading	Longitudinal	233.21 (80)	< .01	0.06 (0.05 to 0.07)	0.95	0.94	Pass (Δ CFI = 0.01)
3. Intercept	Longitudinal	127.40 (70)	< .01	0.04 (0.03 to 0.05)	0.98	0.97	Fail (Δ CFI = 0.03)

Note: Groups considered include samples recruited in schools or online, *RMSEA* Root Mean Square Error of Approximation, *CFI* Comparative Fit Index, *TLI* Tucker-Lewis Index

Table 9

Model fit From Configural, Loading, and Intercept Measurement Invariance Models for Between-Sample Invariance Tests for Intentional Self-regulation and Prosocial Socialization

Model	Type	Chi-square (*df*)	*p*	RMSEA [90% CI]	CFI	TLI	Pass? (Δ CFI ≤ .01)
ISR, *N* = 552							
1. Configural	Group	213.89 (63)	< .01	0.09 (0.08 to 0.11)	0.92	0.91	
2. Loading	Group	213.62 (62)	< .01	0.09 (0.08 to 0.11)	0.92	0.91	Pass (Δ CFI = 0.00)
3. Intercept	Group	243.21 (70)	< .01	0.10 (0.08 to 0.11)	0.91	0.91	Pass (Δ CFI = 0.01)
Prosocial socialization, *N* =552							
1. Configural	Group	7.86 (8)	.45	0.00 (0.00 to 0.07)	1.00	1.00	
2. Loading	Group	4.74 (7)	.69	0.00 (0.00 to 0.06)	1.00	1.01	Pass (Δ CFI = 0.00)
3. Intercept	Group	14.76 (10)	.14	0.04 (0.00 to 0.08)	0.99	0.99	Pass (Δ CFI = 0.01)

Note: Groups considered include samples recruited in schools or online, *ISR* Intentional Self-regulation, RMSEA Root Mean Square Error of Approximation, *CFI* Comparative Fit Index, *TLI* Tucker-Lewis Index

Table 10

Honesty Class Enumeration and Comparison Across Variance-Covariance Specifications (n = 552)

1	2	3	4	5	6	7	8	9	10	11
Σ_K	# of classes (K —	*LL*	*npar*	BIC	CAIC	AWE	Adj LMR -LRT *p*-value (H_0: K classes; H_1: K+1 classes)	$\hat{B}F_{K,K\Downarrow 1}$	$cm\hat{P}_k$	$cm\hat{P}.$
Latent class growth analysis	1	-1727.40	5.00	3486.80	3473.51	3497.22		0.00	0.00	
	2	-1624.76	8.00	3300.03	3279.46	3317.40	< .01	0.01	0.00	
	3	-1610.58	11.00	3290.60	3262.31	3314.47	.06	0.64	0.00	
	4	-1600.65	14.00	3289.70	3253.69	3320.08	.17	0.00	0.00	
	5	-1228.40	17.00	2564.13	2520.41	2601.02	.19	0.00	0.00	
	6	**-834.33**	**20.00**	**1794.93**	**1743.49**	**1838.33**	**.55**	**24.47**	**0.96**	**0.91**
	7	-828.05	23.00	1801.32	1742.17	1851.24	—[b]		0.04	
	8	Not well identified								
Diagonal and class-invariant	1	-1620.91	7.00	3286.01	3268.01	3301.20		0.08	0.00	
	2[a]	-1621.11	9.00	3281.04	3275.90	3318.58	.03	3.54	0.00	
	3	-1603.91	12.00	3283.57	3252.71	3309.62	.13	479.14	0.00	
	4	-1600.61	15.00	3295.92	3257.34	3328.47	.28	390.92	0.00	
	5	-1597.11	18.00	3307.85	3261.56	3346.92	.65	0.00	0.00	
	6	-833.43	21.00	1799.44	1745.44	1845.02	.16	9696.30	1.00	0.09
	7	-833.14	24.00	1817.80	1756.08	1869.89	—[b]	24.19	0.00	
	8	-826.85	27.00	1824.17	1754.74	1882.77	.76	8014.44	0.00	
	9	-826.37	30.00	1842.15	1765.00	1907.26	—[b]		0.00	
	10	Not well identified								

Note: Dotted lines around the full box represent the final chosen model, solid lines around the full box represent the other final candidate model considered with the final model, a solid box around the number of classes only represents the best model within the Σ_K, *LL* Log-likelihood, *npar* number of parameters estimated, *BIC* Bayesian Information Criteria, *CAIC* Consistent Akaike's Information Criteria, *AWE* Approximate Weight of Evidence Criterion, *Adj LMR-LRT p-value* Adjusted Lo-Mendell-Rubin-Likelihood Ratio Test *p*-value, $\hat{B}F_{K,K\Downarrow 1}$ approximate Bayes Factor, $cm\hat{P}_k$ Correct model probability across all within Σ_K models, $cm\hat{P}.$ Correct model probability between Σ_K models.

[a]Slope variance fixed to zero in this and subsequent models in this Σ_K, [b]Could not be estimated

Table 10 (continued)

1	2	3	4	5	6	7	8	9	10	11
Σ_K	# of classes (K —	LL	$npar$	BIC	CAIC	AWE	Adj LMR -LRT p-value (H_0: K classes; H_1: K+1 classes)	$\hat{B}F_{K,K\Downarrow 1}$	$cm\hat{P}_k$	$cm\hat{P}.$
Non-diagonal and class-invariant	1	-1620.42	8.00	3291.35	3270.78	3308.71			1.00	0.00
	2	Not well identified								
Diagonal and class-varying	1	-1620.91	7.00	3286.01	3268.01	3301.20			1.00	0.00
	2	Not well identified								
Non-diagonal and class-varying	1	-1620.42	8.00	3291.35	3270.78	3308.71			1.00	0.00
	2	Not well identified								

Note: Dotted lines around the full box represent the final chosen model, solid lines around the full box represent the other final candidate model considered with the final model, a solid box around the number of classes only represents the best model within the Σ_K, *LL* Log-likelihood, *npar* number of parameters estimated, *BIC* Bayesian Information Criteria, *CAIC* Consistent Akaike's Information Criteria, *AWE* Approximate Weight of Evidence Criterion, *Adj LMR-LRT p-value* Adjusted Lo-Mendell-Rubin-Likelihood Ratio Test p-value, $\hat{B}F_{K,K\Downarrow 1}$ approximate Bayes Factor, $cm\hat{P}_k$ Correct model probability across all within Σ_K models, $cm\hat{P}.$ Correct model probability between Σ_K models.

[a]Slope variance fixed to zero in this and subsequent models in this Σ_K, [b]Could not be estimated

Table 11

Honesty: Model Classification Diagnostics for the Six-class Latent Class Growth Analysis (n = 552)

Class *k*	$\hat{\pi}_k$	$mcaP_k$	$AvePP_k$	OCC_k
Class 1	0.43	0.43	0.99	191.70
Class 2	0.19	0.25	0.72	10.88
Class 3	0.02	0.01	0.87	263.83
Class 4	0.21	0.22	0.95	70.88
Class 5	0.09	0.03	0.69	22.14
Class 6	0.06	0.06	0.99[a]	156180.16

Note: $\hat{\pi}_k$ Model estimated class proportion, $mcaP_k$ Modal class assignment proportion, $AvePP_k$ Average posterior class probability, OCC_k Odds of correct classification ratio
[a]$AvePP_k$ was estimated as 1.00 by the model but was rounded down for OCC_k estimation

Table 12

Honesty: Model Classification Diagnostics for the Six-class Growth Mixture Model with Diagonal Class-invariant Σ_K *(n = 552)*

Class *k*	$\hat{\pi}_k$	$mcaP_k$	$AvePP_k$	OCC_k
Class 1	0.06	0.06	0.99[a]	15603.96
Class 2	0.35	0.39	0.87	12.31
Class 3	0.28	0.28	0.99	426.95
Class 4	0.07	0.03	0.76	39.60
Class 5	0.21	0.22	0.95	77.92
Class 6	0.02	0.02	0.79	150.88

Note: $\hat{\pi}_k$ Model estimated class proportion, $mcaP_k$ Modal class assignment proportion, $AvePP_k$ Average posterior class probability, OCC_k Odds of correct classification ratio

[a] $AvePP_k$ was estimated as 1.00 by the model but was rounded down for OCC_k estimation

Table 13

Honesty Model-estimated, Class-specific Means with Corresponding 95% Confidence Intervals Based on the Six-class Latent Class Growth Analysis (n=552)

Class	Variable	Mean ($\hat{\alpha}_{mk}$)
Class 1 (45.21%) High and relatively consistent	(1) *Intercept*	4.00 (4.00, 4.00)
	(2) *Slope*	0.03 (-0.02, 0.08)
Class 2 (26.44%) Moderate and increasing	(1) *Intercept*	3.00 (3.00, 3.00)
	(2) *Slope*	0.39 (0.06, 0.72)
Class 3 (1.53%) High and decreasing more steeply	(1) *Intercept*	5.00 (5.00, 5.00)
	(2) *Slope*	-1.40 (-1.59, -1.03)
Class 4 (23.18%) High and decreasing	(1) *Intercept*	5.00 (5.00, 5.00)
	(2) *Slope*	-0.33 (-0.41, -0.25)
Class 5 (3.07%) Moderate and relatively consistent	(1) *Intercept*	3.00 (3.00, 3.00)
	(2) *Slope*	0.04 (-0.54, 0.62)
Class 6 (6.32%) Low and increasing	(1) *Intercept*	1.94 (1.86, 2.02)
	(2) *Slope*	0.73 (0.51, 0.95)

Note. $\hat{\alpha}_{mk}$ 95% Confidence interval

Table 14

Humility Class Enumeration and Comparison Across Variance-Covariance Specifications (n = 552)

1	2	3	4	5	6	7	8	9	10	11
Σ_K	# of classes (K —	*LL*	*npar*	BIC	CAIC	AWE	Adj LMR -LRT *p*-value (H_0: K classes; H_1: K+1 classes)	$\hat{B}F_{K,K\Downarrow1}$	$cm\hat{P}_k$	$cm\hat{P}.$
Latent class growth analysis	1	-1648.93	5.00	3329.42	3316.57	3340.28		0.00	0.00	
	2	-1527.61	8.00	3105.74	3085.16	3123.10	< .01	0.00	0.00	
	3	-1496.31	11.00	3062.08	3033.79	3085.95	.02	0.00	0.00	
	4	-1479.97	14.00	3048.33	3012.33	3078.71	.08	0.05	0.00	
	5	-1467.58	17.00	3042.48	2998.76	3079.38	.28	0.00	0.00	
	6	**-1452.69**	**20.00**	**3031.64**	**2980.21**	**3075.05**	**.16**	**12.03**	**0.79**	**0.85**
	7	-1445.70	23.00	3036.62	2977.47	3086.53	.70	0.48	0.07	
	8	-1435.50	26.00	3035.14	2968.28	3091.57			0.14	
	9	Not well identified								
Diagonal and class-invariant	1[a]	-1520.08	6.00	3078.05	3062.62	3091.07		0.00	0.00	
	2	-1502.63	9.00	3062.09	3038.94	3081.62	.04	0.01	0.00	
	3	-1488.56	12.00	3052.89	3022.03	3078.93	.08	0.13	0.00	
	4	-1477.03	15.00	3048.76	3010.19	3081.32	.76	1.02	0.00	
	5	-1467.58	18.00	3048.79	3002.50	3087.86	.22	0.00	0.00	
	6	-1451.76	21.00	3036.11	2982.10	3081.68	.20	0.61	0.38	
	7	-1441.79	24.00	3035.11	2973.39	3087.20	.12		0.62	0.15
	8	Not well identified								

Note: Dotted lines around the full box represent the final chosen model, solid lines around the full box represent the other final candidate model considered with the final model, a solid box around the number of classes only represents the best model within the Σ_K, *LL* Log-likelihood, *npar* number of parameters estimated, *BIC* Bayesian Information Criteria, *CAIC* Consistent Akaike's Information Criteria, *AWE* Approximate Weight of Evidence Criterion, *Adj LMR-LRT p-value* Adjusted Lo-Mendell-Rubin-Likelihood Ratio Test *p*-value, $\hat{B}F_{K,K\Downarrow1}$ approximate Bayes Factor, $cm\hat{P}_k$ Correct model probability across all within Σ_K models, $cm\hat{P}.$ Correct model probability between Σ_K models.

[a]Slope variance fixed to zero in this and subsequent models in this Σ_K, [b]Intercept variance fixed to zero in one class in this and subsequent models in this Σ_K

Table 14 (continued)

1	2	3	4	5	6	7	8	9	10	11
Σ_K	# of classes (K —	*LL*	*npar*	BIC	CAIC	AWE	Adj LMR -LRT p-value (H_0: K classes; H_1: K+1 classes)	$\hat{B}F_{K,K\Downarrow 1}$	$cm\hat{P}_k$	$cm\hat{P}.$
Non-diagonal and class-invariant	1[a]	-1512.38	8.00	3075.27	3054.70	3092.64		0.01	0.00	
	2	-1497.70	11.00	3064.84	3036.56	3088.72	.06	0.02	0.00	
	3	-1484.29	14.00	3056.96	3020.96	3087.34	.02	0.27	0.21	
	4	-1473.49	17.00	3054.31	3010.59	3091.21	.03		0.79	0.00
	5	Not well identified								
Diagonal and class-varying	1[a]	-1520.08	6.00	3078.05	3062.62	3091.07		0.00	0.00	
	2[b]	-1498.93	9.00	3054.69	3031.54	3074.22	.09		0.79	0.00
	3	Not well identified								
Non-diagonal and class-varying	1	-1512.38	8.00	3075.27	3054.70	3092.64			1.00	0.00
	2	Not well identified								

Note: Dotted lines around the full box represent the final chosen model, solid lines around the full box represent the other final candidate model considered with the final model, a solid box around the number of classes only represents the best model within the Σ_K, *LL* Log-likelihood, *npar* number of parameters estimated, *BIC* Bayesian Information Criteria, *CAIC* Consistent Akaike's Information Criteria, *AWE* Approximate Weight of Evidence Criterion, *Adj LMR-LRT p-value* Adjusted Lo-Mendell-Rubin-Likelihood Ratio Test p-value, $\hat{B}F_{K,K\Downarrow 1}$ approximate Bayes Factor, $cm\hat{P}_k$ Correct model probability across all within Σ_K models, $cm\hat{P}.$ Correct model probability between Σ_K models.

[a]Slope variance fixed to zero in this and subsequent models in this Σ_K, [b]Intercept variance fixed to zero in one class in this and subsequent models in this Σ_K

Table 15

Humility: Model Classification Diagnostics for the Six-class Latent Class Growth Analysis (n = 552)

Class k	$\hat{\pi}_k$	$mcaP_k$	$AvePP_k$	OCC_k
Class 1	0.32	0.33	0.89	16.71
Class 2	0.34	0.35	0.81	8.14
Class 3	0.04	0.03	0.80	83.49
Class 4	0.07	0.06	0.90	122.81
Class 5	0.01	0.01	0.99	9835.71
Class 6	0.22	0.22	0.78	13.03

Note: $\hat{\pi}_k$ Model estimated class proportion, $mcaP_k$ Modal class assignment proportion, $AvePP_k$ Average posterior class probability, OCC_k Odds of correct classification ratio

Table 16

Humility: Model Classification Diagnostics for the Seven-class Growth Mixture Model with Diagonal Class-invariant Σ_K (n = 552)

Class *k*	$\hat{\pi}_k$	$mcaP_k$	$AvePP_k$	OCC_k
Class 1	0.31	0.34	0.80	8.72
Class 2	0.01	0.01	0.98	3956.85
Class 3	0.06	0.06	0.88	114.63
Class 4	0.16	0.16	0.82	23.09
Class 5	0.31	0.33	0.90	20.40
Class 6	0.11	0.08	0.66	16.55
Class 7	0.04	0.02	0.91	256.87

Note: $\hat{\pi}_k$ Model estimated class proportion, $mcaP_k$ Modal class assignment proportion, $AvePP_k$ Average posterior class probability, OCC_k Odds of correct classification ratio

Table 17

Humility Model-estimated, Class-specific Means with Corresponding 95% Confidence Intervals based on the Six-class Latent Class Growth Analysis (n=552)

Class	Variable	Mean ($\hat{\alpha}_{mk}$)
Class 1 (32.97%) High and decreasing	(1) *Intercept*	4.78 (4.43, 5.13)
	(2) *Slope*	-0.19 (-0.46, 0.09)
Class 2 (34.78%) Moderate and increasing	(1) *Intercept*	3.89 (3.84, 3.94)
	(2) *Slope*	0.18 (0.12, 0.24)
Class 3 (3.26%) High and decreasing more steeply	(1) *Intercept*	4.67 (4.17, 5.17)
	(2) *Slope*	-1.03 (-1.82, -0.24)
Class 4 (6.34%) Low and increasing	(1) *Intercept*	2.34 (2.25, 2.43)
	(2) *Slope*	0.52 (0.44, 0.60)
Class 5 (0.72%) Low and relatively consistent	(1) *Intercept*	1.62 (1.48, 1.76)
	(2) *Slope*	-0.06 (-0.23, 0.11)
Class 6 (21.92%) Moderate and relatively consistent	(1) *Intercept*	3.33 (3.19, 3.47)
	(2) *Slope*	0.05 (-0.18, 0.28)

Note. $\hat{\alpha}_{mk}$ 95% Confidence intervals

Table 18

Diligence Class Enumeration and Comparison across Variance-Covariance Specifications (n=552)

1	2	3	4	5	6	7	8	9	10	11
Σ_K	# of classes (K —	*LL*	*npar*	BIC	CAIC	AWE	Adj LMR -LRT *p*-value (H_0: K classes; H_1: K+1 classes)	$\hat{B}F_{K,K\Downarrow 1}$	$cm\hat{P}_k$	$cm\hat{P}.$
Latent class growth analysis	1	-1749.66	5.00	3530.89	3518.03	3541.74		0.00	0.00	
	2	-1638.69	8.00	3327.88	3307.31	3345.25	< .01	0.00	0.00	
	3	-1614.84	11.00	3299.14	3270.85	3323.01	.01	0.35	0.26	
	4	**-1604.33**	**14.00**	**3297.05**	**3261.05**	**3327.43**	**.19**	**53.38**	**0.72**	**0.09**
	5	-1598.84	17.00	3305.00	3261.28	3341.90	.40	3.36	0.01	
	6	-1590.58	20.00	3307.43	3255.99	3350.83	.48	2.34	0.00	
	7	-1581.96	23.00	3309.13	3249.98	3359.05	.48	31.45	0.00	
	8	-1575.94	26.00	3316.03	3249.16	3372.45	.71	0.42	0.00	
	9	-1565.59	29.00	3314.27	3239.70	3377.21	.03	0.39	0.00	
	10	-1555.19	32.00	3312.41	3230.12	3381.86	.05	607.29	0.00	
	11	-1552.13	35.00	3325.23	3235.22	3401.19	.35		0.00	
	12	Not well identified								
Diagonal and class-invariant	1	-1640.30	7.00	3324.80	3306.79	3339.99		0.00	0.00	
	2	-1614.69	10.00	3292.51	3266.80	3314.22	< .01	5.19	0.79	0.86
	3	-1606.87	13.00	3295.81	3262.38	3324.02	.07	3.87	0.15	
	4	-1598.75	16.00	3298.51	3257.37	3333.24	.03	2.44	0.04	
	5	-1590.17	19.00	3300.30	3251.44	3341.53	.31		0.02	
	6	Not well identified								

Note: Dotted lines around the full box represent the final chosen model, solid lines around the full box represent the other final candidate model considered with the final model, a solid box around the number of classes only represents the best model within the Σ_K, *LL* Log-likelihood, *npar* number of parameters estimated, *BIC* Bayesian Information Criteria, *CAIC* Consistent Akaike's Information Criteria, *AWE* Approximate Weight of Evidence Criterion, *Adj LMR-LRT p-value* Adjusted Lo-Mendell-Rubin-Likelihood Ratio Test *p*-value, $\hat{B}F_{K,K\Downarrow 1}$ approximate Bayes Factor, $cm\hat{P}_k$ Correct model probability across all within Σ_K models, $cm\hat{P}.$ Correct model probability between Σ_K models.

Table 18 (continued)

1	2	3	4	5	6	7	8	9	10	11
Σ_K	# of classes (K —	LL	$npar$	BIC	CAIC	AWE	Adj LMR -LRT p-value (H_0: K classes; H_1: K+1 classes)	$\hat{B}F_{K,K\Downarrow 1}$	$cm\hat{P}_k$	$cm\hat{P}.$
Non-diagonal and class-invariant	1	-1637.80	8.00	3326.11	3305.54	3343.47		0.00	0.00	
	2	-1614.52	11.00	3298.50	3270.21	3322.37	< .01	5.80	0.85	0.04
	3	-1606.81	14.00	3302.01	3266.01	3332.40			0.15	
	4	Not well identified								
Diagonal and class-varying	1	-1640.30	7.00	3324.80	3306.79	3339.99		0.00	0.00	
	2	-1613.65	12.00	3303.07	3272.21	3329.11	.03		1.00	0.00
	3	Not well identified								
Non-diagonal and class-varying	1	-1637.80	8.00	3326.11	3305.54	3343.47		0.00	1.00	0.00
	2	Not well identified								

Note: Dotted lines around the full box represent the final chosen model, solid lines around the full box represent the other final candidate model considered with the final model, a solid box around the number of classes only represents the best model within the Σ_K, *LL* Log-likelihood, *npar* number of parameters estimated, *BIC* Bayesian Information Criteria, *CAIC* Consistent Akaike's Information Criteria, *AWE* Approximate Weight of Evidence Criterion, *Adj LMR-LRT p-value* Adjusted Lo-Mendell-Rubin-Likelihood Ratio Test p-value, $\hat{B}F_{K,K\Downarrow 1}$ approximate Bayes Factor, $cm\hat{P}_k$ Correct model probability across all within Σ_K models, $cm\hat{P}.$ Correct model probability between Σ_K models.

Table 19

Diligence: Model Classification Diagnostics for the Four-class Latent Class Growth Analysis (n = 552)

Class k	$\hat{\pi}_k$	$mcaP_k$	$AvePP_k$	OCC_k
Class 1	0.10	0.10	0.86	50.38
Class 2	0.08	0.04	0.76	35.74
Class 3	0.49	0.52	0.85	5.86
Class 4	0.33	0.34	0.76	6.59

Note: $\hat{\pi}_k$ Model estimated class proportion, $mcaP_k$ Modal class assignment proportion, $AvePP_k$ Average posterior class probability, OCC_k Odds of correct classification ratio

Table 20

Diligence: Model Classification Diagnostics for the Two-class Growth Mixture Model with Diagonal Class-invariant Σ_K *(n = 552)*

Class *k*	$\hat{\pi}_k$	$mcaP_k$	$AvePP_k$	OCC_k
Class 1	0.80	0.82	0.94	3.76
Class 2	0.20	0.18	0.81	17.23

Note: $\hat{\pi}_k$ Model estimated class proportion, $mcaP_k$ Modal class assignment proportion, $AvePP_k$ Average posterior class probability, OCC_k Odds of correct classification ratio

Table 21

Diligence Model-estimated, Class-specific Means with Corresponding 95% Confidence Intervals Based on the Four-class Latent Class Growth Analysis (n=552)

Class	Variable	Mean ($\hat{\alpha}_{mk}$)
Class 1 (9.96%)	(1) *Intercept*	2.28 (1.97, 2.60)
Low and increasing	(2) *Slope*	0.37 (0.15, 0.60)
Class 2 (4.35%)	(1) *Intercept*	4.18 (3.83, 4.53)
High and decreasing	(2) *Slope*	-0.78 (-1.16, -0.40)
Class 3 (52.17%)	(1) *Intercept*	4.46 (4.33, 4.59)
High and relatively consistent	(2) *Slope*	-0.05 (-0.17, 0.07)
Class 4 (33.51%)	(1) *Intercept*	3.45 (3.23, 3.67)
Moderate and increasing	(2) *Slope*	0.14 (0.01, 0.27)

Note. $\hat{\alpha}_{mk}$ 95% Confidence interval

Table 22

Future mindedness Class Enumeration and Comparison Across Variance-Covariance Specifications (n = 551)

1	2	3	4	5	6	7	8	9	10	11
Σ_K	# of classes (K —	*LL*	*npar*	BIC	CAIC	AWE	Adj LMR -LRT *p*-value (H_0: K classes; H_1: K+1 classes)	$\hat{B}F_{K,K\Downarrow 1}$	$cm\hat{P}_k$	$cm\hat{P}.$
Latent class growth analysis	1	-1846.39	5.00	3724.33	3711.48	3735.18		0.00	0.00	
	2	-1742.05	8.00	3534.60	3514.03	3551.96	< .01	0.00	0.00	
	3	-1722.55	11.00	3514.53	3486.26	3538.41	.02	0.89	0.46	
	4	**-1712.97**	**14.00**	**3514.31**	**3478.32**	**3544.70**	**.03**	**108.09**	**0.51**	**0.02**
	5	-1708.19	17.00	3523.68	3479.98	3560.58	.08	0.23	0.00	
	6	-1697.25	20.00	3520.74	3469.32	3564.15	.30	35.43	0.02	
	7	-1691.35	23.00	3527.87	3468.75	3577.79	.14		0.00	
	8	Not well identified								
Diagonal and class-invariant	1[a]	-1736.22	6.00	3510.31	3494.89	3523.34		0.15	0.12	
	2	-1724.86	9.00	3506.53	3483.40	3526.07	.03	12.00	0.80	0.85
	3	-1717.88	12.00	3511.50	3480.65	3537.55	.07	9.73	0.07	
	4	-1710.69	15.00	3516.05	3477.49	3548.61	.01	55.12	0.01	
	5	-1705.23	18.00	3524.07	3477.80	3563.14	.31	696.10	0.00	
	6	-1702.31	21.00	3537.16	3483.18	3582.74	.06	0.08	0.00	
	7	-1690.29	24.00	3532.07	3470.37	3584.16	.11	10.61	0.00	
	8	-1683.19	27.00	3536.79	3467.39	3595.40	.12	-	0.00	
	9	Not well identified								

Note: Dotted lines around the full box represent the final chosen model, solid lines around the full box represent the other final candidate model considered with the final model, a solid box around the number of classes only represents the best model within the Σ_K, *LL* Log-likelihood, *npar* number of parameters estimated, *BIC* Bayesian Information Criteria, *CAIC* Consistent Akaike's Information Criteria, *AWE* Approximate Weight of Evidence Criterion, *Adj LMR-LRT p-value* Adjusted Lo-Mendell-Rubin-Likelihood Ratio Test p-value, $\hat{B}F_{K,K\Downarrow 1}$ approximate Bayes Factor, $cm\hat{P}_k$ Correct model probability across all within Σ_K models, $cm\hat{P}.$ Correct model probability between Σ_K models.

[a]Slope variance fixed to zero in this and subsequent models in this Σ_K

Table 22 (continued)

1	2	3	4	5	6	7	8	9	10	11
Σ_K	# of classes (K —	*LL*	*npar*	BIC	CAIC	AWE	Adj LMR -LRT *p*-value (H_0: K classes; H_1: K+1 classes)	$\hat{B}F_{K,K\Downarrow 1}$	$cm\hat{P}_k$	$cm\hat{P}.$
Non-diagonal and class-invariant	1	Not well identified								
Diagonal and class-varying	1[a]	-1736.22	6.00	3510.31	3494.89	3523.34		2.90	0.74	0.13
	2	-1724.66	10.00	3512.45	3486.74	3534.15	.27	50.83	0.25	
	3	-1715.97	14.00	3520.30	3484.31	3550.69	.04		0.01	
	4	Not well identified								
Non-diagonal and class-varying	1	Not well identified								

Note: Dotted lines around the full box represent the final chosen model, solid lines around the full box represent the other final candidate model considered with the final model, a solid box around the number of classes only represents the best model within the Σ_K, *LL* Log-likelihood, *npar* number of parameters estimated, *BIC* Bayesian Information Criteria, *CAIC* Consistent Akaike's Information Criteria, *AWE* Approximate Weight of Evidence Criterion, *Adj LMR-LRT p-value* Adjusted Lo-Mendell-Rubin-Likelihood Ratio Test p-value, $\hat{B}F_{K,K\Downarrow 1}$ approximate Bayes Factor, $cm\hat{P}_k$ Correct model probability across all within Σ_K models, $cm\hat{P}.$ Correct model probability between Σ_K models.

[a]Slope variance fixed to zero in this and subsequent models in this Σ_K

Table 23

Future Mindedness: Model Classification Diagnostics for the Four-class Latent Class Growth Analysis (n = 551)

Class k	$\hat{\pi}_k$	$mcaP_k$	$AvePP_k$	OCC_k
Class 1	0.44	0.45	0.79	4.86
Class 2	0.34	0.26	0.79	7.23
Class 3	0.06	0.03	0.74	44.92
Class 4	0.16	0.15	0.87	34.51

Note: $\hat{\pi}_k$ Model estimated class proportion, $mcaP_k$ Modal class assignment proportion, $AvePP_k$ Average posterior class probability, OCC_k Odds of correct classification ratio

Table 24

Future Mindedness: Model Classification Diagnostics for the Two-class Growth Mixture Model with Diagonal Class-invariant Σ_K *(n = 551)*

Class *k*	$\hat{\pi}_k$	$mcaP_k$	$AvePP_k$	OCC_k
Class 1	0.79	0.82	0.92	2.93
Class 2	0.21	0.18	0.80	14.43

Note: $\hat{\pi}_k$ Model estimated class proportion, $mcaP_k$ Modal class assignment proportion, $AvePP_k$ Average posterior class probability, OCC_k Odds of correct classification ratio

Table 25

Future Mindedness Model-estimated, Class-specific Means with Corresponding 95% Confidence Intervals Based on the Four-class Latent Class Growth Analysis (n=551)

Class	Variable	Mean ($\hat{\alpha}_{mk}$)
Class 1 (45.01%) Moderate and increasing	(1) *Intercept*	3.42 (3.21, 3.63)
	(2) *Slope*	0.17 (0.07, 0.27)
Class 2 (36.12%) High and relatively consistent	(1) *Intercept*	4.41 (4.28, 4.54)
	(2) *Slope*	-0.01 (-0.12, 0.10)
Class 3 (3.45%) High and decreasing	(1) *Intercept*	4.44 (4.10, 4.78)
	(2) *Slope*	-0.87 (-1.32, -0.42)
Class 4 (15.43%) Low and increasing	(1) *Intercept*	2.30 (2.07, 2.53)
	(2) *Slope*	0.16 (0.04, 0.28)

Note. $\hat{\alpha}_{mk}$ 95% Confidence interval

Table 26

Purpose Class Enumeration and Comparison Across Variance-Covariance Specifications (n = 549)

1	2	3	4	5	6	7	8	9	10	11
Σ_K	# of classes (K —	*LL*	*npar*	BIC	CAIC	AWE	Adj LMR -LRT *p*-value (H_0: K classes; H_1: K+1 classes)	$\hat{B}F_{K,K\Downarrow1}$	$cm\hat{P}_k$	$cm\hat{P}.$
Latent class growth analysis	1	-1513.22	5.00	3057.98	3045.14	3068.84		0.00	0.00	
	2	-1356.27	8.00	2763.00	2742.45	2780.37	< .01	0.00	0.00	
	3	-1308.30	11.00	2685.99	2657.74	2709.87	< .01	2.56	0.01	
	4	-1299.78	14.00	2687.88	2651.92	2718.27	.35	0.48	0.01	
	5	-1289.42	17.00	2686.42	2642.41	2722.98	.54	0.02	0.01	
	6	**-1276.10**	**20.00**	**2678.36**	**2626.99**	**2721.78**	**.15**	**3.17**	**0.65**	**0.17**
	7	-1267.79	23.00	2680.67	2621.59	2730.60	.01	1.70	0.20	
	8	-1258.86	26.00	2681.74	2614.95	2738.18	.18	480.82	0.12	
	9	-1255.58	29.00	2694.09	2619.60	2757.05	.57	152.47	0.00	
	10	-1251.14	32.00	2704.14	2621.95	2773.61	.27	58.41	0.00	
	11	-1245.75	35.00	2712.28	2622.38	2788.26	.16	12197.67	0.00	
	12	-1245.69	38.00	2731.09	2633.49	2813.59	.80	6.41	0.00	
	13	-1238.09	41.00	2734.81	2629.50	2823.82	.20	219.20	0.00	
	14	-1234.02	44.00	2745.59	2632.58	2841.12	.37		0.00	
	15	Not well identified								

Note: Dotted lines around the full box represent the final chosen model, solid lines around the full box represent the other final candidate model considered with the final model, a solid box around the number of classes only represents the best model within the Σ_K, *LL* Log-likelihood, *npar* number of parameters estimated, *BIC* Bayesian Information Criteria, *CAIC* Consistent Akaike's Information Criteria, *AWE* Approximate Weight of Evidence Criterion, *Adj LMR-LRT p-value* Adjusted Lo-Mendell-Rubin-Likelihood Ratio Test *p*-value, $\hat{B}F_{K,K\Downarrow1}$ approximate Bayes Factor, $cm\hat{P}_k$ Correct model probability across all within Σ_K models, $cm\hat{P}.$ Correct model probability between Σ_K models.

[a]Slope variance fixed to zero in this and subsequent models in this Σ_K

Table 26 (continued)

1	2	3	4	5	6	7	8	9	10	11
Σ_K	# of classes (K —	LL	$npar$	BIC	CAIC	AWE	Adj LMR -LRT p-value (H_0: K classes; H_1: K+1 classes)	$\hat{B}F_{K,K\Downarrow1}$	$cm\hat{P}_k$	$cm\hat{P}.$
Diagonal and class-invariant	1[a]	-1323.66	6.00	2685.18	2669.77	2698.20		0.04	0.02	
	2	-1310.98	9.00	2678.73	2655.61	2698.27	.33	6.65	0.60	0.14
	3	-1303.41	12.00	2682.51	2651.69	2708.57	.22	0.33	0.09	
	4	-1292.83	15.00	2680.28	2641.75	2712.84	.39	51.78	0.28	
	5	-1287.31	18.00	2688.17	2641.94	2727.25	.72		0.01	
	6	Not well identified								
Non-diagonal and class-invariant	1	-1319.70	8.00	2689.87	2669.32	2707.24		0.01	0.00	
	2	-1305.86	11.00	2681.11	2652.86	2705.00	.09	0.06	0.06	
	3	-1293.66	14.00	2675.64	2639.68	2706.03	.01		0.94	0.68
	4	Not well identified								
Diagonal and class-varying	1[a]	-1323.66	6.00	2685.18	2669.77	2698.20			1.00	0.01
	2	Not well identified								
Non-diagonal and class-varying	1	-1319.70	8.00	2689.87	2669.32	2707.24			1.00	0.00
	2	Not well identified								

Note: Dotted lines around the full box represent the final chosen model, solid lines around the full box represent the other final candidate model considered with the final model, a solid box around the number of classes only represents the best model within the Σ_K, *LL* Log-likelihood, *npar* number of parameters estimated, *BIC* Bayesian Information Criteria, *CAIC* Consistent Akaike's Information Criteria, *AWE* Approximate Weight of Evidence Criterion, *Adj LMR-LRT p-value* Adjusted Lo-Mendell-Rubin-Likelihood Ratio Test p-value, $\hat{B}F_{K,K\Downarrow1}$ approximate Bayes Factor, $cm\hat{P}_k$ Correct model probability across all within Σ_K models, $cm\hat{P}.$ Correct model probability between Σ_K models.

[a]Slope variance fixed to zero in this and subsequent models in this Σ_K

Table 27

Purpose: Model Classification Diagnostics for the Six-class Latent Class Growth Analysis (n = 549)

Class k	$\hat{\pi}_k$	$mcaP_k$	$AvePP_k$	OCC_k
Class 1	0.16	0.12	0.74	15.16
Class 2	0.06	0.05	0.87	111.93
Class 3	0.24	0.25	0.87	21.05
Class 4	0.01	0.01	0.98	5695.76
Class 5	0.31	0.32	0.91	22.26
Class 6	0.22	0.24	0.69	7.61

Note: $\hat{\pi}_k$ Model estimated class proportion, $mcaP_k$ Modal class assignment proportion, $AvePP_k$ Average posterior class probability, OCC_k Odds of correct classification ratio

Table 28

Purpose: Model Classification Diagnostics for the Three-class Growth Mixture Model with Non-diagonal Class-invariant Σ_K (n = 549)

Class *k*	$\hat{\pi}_k$	$mcaP_k$	$AvePP_k$	OCC_k
Class 1	0.31	0.34	0.80	8.72
Class 2	0.01	0.01	0.98	3956.85
Class 3	0.06	0.06	0.88	114.63

Note: $\hat{\pi}_k$ Model estimated class proportion, $mcaP_k$ Modal class assignment proportion, $AvePP_k$ Average posterior class probability, OCC_k Odds of correct classification ratio

Table 29

Purpose Model-estimated, Class-specific Means with Corresponding 95% Confidence Intervals based on the Six-class Latent Class Growth Analysis (n=549)

Class	Variable	Mean ($\hat{\alpha}_{mk}$)
Class 1 (12.20%) High and decreasing more steeply	(1) *Intercept*	4.14 (4.02, 4.26)
	(2) *Slope*	-0.42 (-0.60, -0.24)
Class 2 (0.55%) Low and relatively consistent	(1) *Intercept*	2.58 (2.28, 2.88)
	(2) *Slope*	0.19 (-0.09, 0.47)
Class 3 (24.95%) Moderate and increasing	(1) *Intercept*	3.28 (3.19, 3.37)
	(2) *Slope*	0.15 (0.07, 0.23)
Class 4 (0.09%) Low and increasing	(1) *Intercept*	1.64 (1.32, 1.96)
	(2) *Slope*	0.38 (0.07, 0.69)
Class 5 (32.24%) High and decreasing	(1) *Intercept*	4.77 (4.72, 4.82)
	(2) *Slope*	-0.19 (-0.25, -0.13)
Class 6 (24.23%) High and increasing	(1) *Intercept*	4.01 (3.90, 4.12)
	(2) *Slope*	0.11 (-0.02, 0.24)

Note. $\hat{\alpha}_{mk}$ 95% Confidence interval

Table 30

Correlations for Class-Level Predicted Character Attributes at Each Time Point

Measure	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Honesty Wave 2	3.83	0.86	—														
2. Humility Wave 2	3.97	0.73	.26	—													
3. Diligence Wave 2	3.89	0.70	.31	.39	—												
4. Future Mindedness Wave 2	3.64	0.73	.28	.40	.47	—											
5. Purpose Wave 2	3.99	0.70	.22	.44	.35	.38	—										
6. Honesty Wave 3	3.89	0.56	.97	.25	.31	.27	.22	—									
7. Humility Wave 3	3.98	0.58	.26	.94	.39	.41	.42	.27	—								
8. Diligence Wave 3	3.92	0.58	.31	.37	.96	.47	.34	.32	.39	—							
9. Future Mindedness Wave 3	3.71	0.65	.29	.40	.46	.97	.37	.30	.43	.47	—						
10. Purpose Wave 3	3.95	0.56	.21	.44	.35	.40	.98	.22	.43	.35	.40	—					
11. Honesty Wave 4	3.96	0.36	.64	.18	.22	.18	.16	.81	.23	.26	.23	.18	—				
12. Humility Wave 4	3.99	0.53	.21	.67	.31	.35	.31	.24	.88	.34	.39	.34	.25	—			
13. Diligence Wave 4	3.94	0.52	.27	.29	.79	.40	.29	.30	.34	.93	.43	.31	.29	.34	—		
14. Future Mindedness Wave 4	3.77	0.62	.28	.37	.40	.85	.33	.30	.42	.44	.95	.37	.27	.41	.44	—	
15. Purpose Wave 4	3.92	0.49	.19	.38	.31	.37	.81	.20	.40	.32	.39	.93	.19	.34	.30	.37	—

Note: All coefficients are significant at $p < .001$

Table 31

Honesty Six-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 552), Reference class 1

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1 (ref)	High and relatively consistent	0.00			1.00
Class 2	Moderate and increasing	0.08	0.29	.777	1.09
Class 3	High and decreasing more steeply	1.02	0.94	.277	2.78
Class 4	High and decreasing	0.52	0.19	.006	1.68
Class 5	Moderate and relatively consistent	-1.13	0.59	.056	0.32
Class 6	Low and increasing	-1.08	-4.22	< .001	0.34
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1 (ref)	High and relatively consistent	0.00			1.00
Class 2	Moderate and increasing	-0.49	0.20	.015	0.61
Class 3	High and decreasing more steeply	-0.39	0.20	.314	0.68
Class 4	High and decreasing	0.18	0.16	.285	1.19
Class 5	Moderate and relatively consistent	0.13	0.16	.285	1.14
Class 6	Low and increasing	0.20	0.28	.647	1.22

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 32

Honesty Six-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 552), Reference class 2

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and relatively consistent	0.08	0.29	.777	1.09
Class 2 (ref)	Moderate and increasing	0.00			1.00
Class 3	High and decreasing more steeply	0.94	0.97	.331	2.56
Class 4	High and decreasing	0.44	0.32	.174	1.55
Class 5	Moderate and relatively consistent	-1.21	0.70	.083	0.30
Class 6	Low and increasing	-1.17	0.39	.003	0.31
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and relatively consistent	0.49	0.20	.015	1.64
Class 2 (ref)	Moderate and increasing	0.00			1.00
Class 3	High and decreasing more steeply	0.10	0.41	.802	1.11
Class 4	High and decreasing	0.67	0.24	.006	1.95
Class 5	Moderate and relatively consistent	0.62	0.39	.109	1.86
Class 6	Low and increasing	0.69	0.33	.034	1.99

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 33

Honesty Six-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 552), Reference class 3

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and relatively consistent	-1.02	0.94	.277	0.36
Class 2	Moderate and increasing	-0.94	0.97	.331	0.39
Class 3 (ref)	High and decreasing more steeply	0.00			1.00
Class 4	High and decreasing	-0.50	1.00	.615	0.60
Class 5	Moderate and relatively consistent	-2.15	1.13	.057	0.12
Class 6	Low and increasing	-2.11	0.97	.031	0.12
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and relatively consistent	0.39	0.39	.314	1.48
Class 2	Moderate and increasing	-0.10	0.41	.802	0.90
Class 3 (ref)	High and decreasing more steeply	0.00			1.00
Class 4	High and decreasing	0.57	0.44	.203	1.76
Class 5	Moderate and relatively consistent	0.52	0.48	.279	1.68
Class 6	Low and increasing	0.59	0.46	.203	1.80

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 34

Honesty Six-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 552), Reference class 4

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and relatively consistent	-0.52	0.18	.006	0.60
Class 2	Moderate and increasing	-0.44	0.32	.174	0.65
Class 3	High and decreasing more steeply	0.50	1.00	.615	1.66
Class 4 (ref)	High and decreasing	0.00			1.00
Class 5	Moderate and relatively consistent	-1.65	0.63	.009	0.19
Class 6	Low and increasing	-1.60	0.30	< .001	0.20
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and relatively consistent	-0.18	0.16	.285	0.84
Class 2	Moderate and increasing	-0.67	0.24	.006	0.51
Class 3	High and decreasing more steeply	-0.57	0.44	.203	0.57
Class 4 (ref)	High and decreasing	0.00			1.00
Class 5	Moderate and relatively consistent	-0.05	0.31	.874	0.95
Class 6	Low and increasing	0.02	0.28	.944	1.02

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 35

Honesty Six-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 552), Reference class 5

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and relatively consistent	1.13	0.59	.056	3.09
Class 2	Moderate and increasing	1.21	0.70	.083	3.36
Class 3	High and decreasing more steeply	2.15	1.13	.057	8.59
Class 4	High and decreasing	1.65	0.63	.009	5.19
Class 5 (ref)	Moderate and relatively consistent	0.00			1.00
Class 6	Low and increasing	0.04	0.59	.941	1.04
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and relatively consistent	-0.13	0.28	.647	0.88
Class 2	Moderate and increasing	-0.62	0.39	.109	0.54
Class 3	High and decreasing more steeply	-0.52	0.48	.279	0.60
Class 4	High and decreasing	0.05	0.31	.874	1.05
Class 5 (ref)	Moderate and relatively consistent	0.00			1.00
Class 6	Low and increasing	0.07	0.34	.841	1.07

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 36

Honesty Six-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 552), Reference class 6

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and relatively consistent	1.08	0.26	< .001	2.96
Class 2	Moderate and increasing	1.17	0.39	.003	3.21
Class 3	High and decreasing more steeply	2.11	0.97	.031	8.23
Class 4	High and decreasing	1.60	0.30	< .001	4.97
Class 5	Moderate and relatively consistent	-0.04	0.59	.941	0.96
Class 6 (ref)	Low and increasing	0.00			1.00
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and relatively consistent	-0.20	0.25	.437	0.82
Class 2	Moderate and increasing	-0.69	0.33	.034	0.50
Class 3	High and decreasing more steeply	-0.59	0.46	.203	0.56
Class 4	High and decreasing	-0.02	0.28	.944	0.98
Class 5	Moderate and relatively consistent	-0.07	0.34	.841	0.93
Class 6 (ref)	Low and increasing	0.00			1.00

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 37

Humility Six-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 552), Reference class 1

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1 (ref)	High and decreasing	0.00			1.00
Class 2	Moderate and increasing	-1.87	0.36	< .001	0.15
Class 3	High and decreasing more steeply	-0.47	0.65	.467	0.62
Class 4	Low and increasing	-4.21	0.56	< .001	0.01
Class 5	Low and relatively consistent	4.32	2.98	.147	75.41
Class 6	Moderate and relatively consistent	-3.03	0.47	< .001	0.05
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1 (ref)	High and decreasing	0.00			1.00
Class 2	Moderate and increasing	-0.26	0.21	.211	0.77
Class 3	High and decreasing more steeply	0.04	0.38	.912	1.04
Class 4	Low and increasing	-0.62	0.29	.031	0.54
Class 5	Low and relatively consistent	-0.74	0.51	.146	0.48
Class 6	Moderate and relatively consistent	-0.55	0.23	.014	0.57

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 38

Humility Six-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 552), Reference class 2

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing	1.87	0.36	< .001	6.48
Class 2 (ref)	Moderate and increasing	0.00			1.00
Class 3	High and decreasing more steeply	1.40	0.60	.019	4.04
Class 4	Low and increasing	-2.35	0.42	< .001	0.10
Class 5	Low and relatively consistent	6.19	3.00	.039	488.33
Class 6	Moderate and relatively consistent	-1.17	0.32	< .001	0.31
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing	0.26	0.21	.211	1.30
Class 2 (ref)	Moderate and increasing	0.00			1.00
Class 3	High and decreasing more steeply	0.30	0.36	.398	1.35
Class 4	Low and increasing	-0.36	0.24	.135	0.70
Class 5	Low and relatively consistent	-0.48	0.54	.366	0.62
Class 6	Moderate and relatively consistent	-0.29	0.19	.121	0.75

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 39

Humility Six-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 552), Reference class 3

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing	0.47	0.65	.467	1.60
Class 2	Moderate and increasing	-1.40	0.60	.019	0.25
Class 3 (ref)	High and decreasing more steeply	0.00			1.00
Class 4	Low and increasing	-3.74	0.73	< .001	0.02
Class 5	Low and relatively consistent	4.79	3.04	.114	120.78
Class 6	Moderate and relatively consistent	-2.56	0.66	< .001	0.08
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing	-0.04	0.38	.912	0.96
Class 2	Moderate and increasing	-0.30	0.36	.398	0.74
Class 3 (ref)	High and decreasing more steeply	0.00			1.00
Class 4	Low and increasing	-0.66	0.41	.105	0.52
Class 5	Low and relatively consistent	-0.79	0.61	.196	0.46
Class 6	Moderate and relatively consistent	-0.60	0.37	.105	0.55

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 40

Humility Six-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 552), Reference class 4

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing	4.21	0.56	< .001	67.56
Class 2	Moderate and increasing	2.35	0.42	< .001	10.43
Class 3	High and decreasing more steeply	3.74	0.73	< .001	42.18
Class 4 (ref)	Low and increasing	0.00			1.00
Class 5	Low and relatively consistent	8.54	3.05	.005	5094.92
Class 6	Moderate and relatively consistent	1.18	0.39	.002	3.25
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing	0.62	0.29	.031	1.85
Class 2	Moderate and increasing	0.36	0.24	.135	1.43
Class 3	High and decreasing more steeply	0.66	0.41	.105	1.93
Class 4 (ref)	Low and increasing	0.00			1.00
Class 5	Low and relatively consistent	-0.13	0.58	.824	0.88
Class 6	Moderate and relatively consistent	0.06	0.23	.788	1.06

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 41

Humility Six-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 552), Reference class 5

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing	-4.32	2.98	.147	0.01
Class 2	Moderate and increasing	-6.19	3.00	.039	0.00
Class 3	High and decreasing more steeply	-4.79	3.04	.114	0.01
Class 4	Low and increasing	-8.54	3.05	.005	0.00
Class 5 (ref)	Low and relatively consistent	0.00			1.00
Class 6	Moderate and relatively consistent	-7.36	3.03	.015	0.00
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing	0.74	0.51	.146	2.10
Class 2	Moderate and increasing	0.48	0.54	.366	1.62
Class 3	High and decreasing more steeply	0.79	0.61	.196	2.19
Class 4	Low and increasing	0.13	0.58	.824	1.14
Class 5 (ref)	Low and relatively consistent	0.00			1.00
Class 6	Moderate and relatively consistent	0.19	0.55	.729	1.21

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 42

Humility Six-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 552), Reference class 6

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing	3.03	0.47	< .001	20.74
Class 2	Moderate and increasing	1.17	0.32	< .001	3.21
Class 3	High and decreasing more steeply	2.56	0.66	< .001	12.95
Class 4	Low and increasing	-1.18	0.39	.002	0.31
Class 5	Low and relatively consistent	7.36	3.03	.015	1565.56
Class 6 (ref)	Moderate and relatively consistent	0.00			1.00
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing	0.55	0.23	.014	1.74
Class 2	Moderate and increasing	0.29	0.19	.121	1.34
Class 3	High and decreasing more steeply	0.60	367.00	.105	1.81
Class 4	Low and increasing	-0.06	0.23	.788	0.94
Class 5	Low and relatively consistent	-0.19	0.55	.729	0.83
Class 6 (ref)	Moderate and relatively consistent	0.00			1.00

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 43

Diligence Four-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 552), Reference class 1

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1 (ref)	Low and increasing	0.00			1.00
Class 2	High and decreasing	6.49	1.43	< .001	655.90
Class 3	High and relatively consistent	6.89	1.08	< .001	986.34
Class 4	Moderate and increasing	3.92	0.93	< .001	50.40
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1 (ref)	Low and increasing	0.00			1.00
Class 2	High and decreasing	-1.18	0.54	.029	0.31
Class 3	High and relatively consistent	-0.74	0.46	.109	0.48
Class 4	Moderate and increasing	-0.88	429.00	.041	0.42

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 44

Diligence Four-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 552), Reference class 2

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	Low and increasing	-6.49	1.43	< .001	0.00
Class 2 (ref)	High and decreasing	0.00			1.00
Class 3	High and relatively consistent	0.41	0.82	.618	1.50
Class 4	Moderate and increasing	-2.57	1.02	.012	0.08
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	Low and increasing	1.18	0.54	.029	3.25
Class 2 (ref)	High and decreasing	0.00			1.00
Class 3	High and relatively consistent	0.44	0.35	.203	1.56
Class 4	Moderate and increasing	0.30	0.38	.417	1.36

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 45

Diligence Four-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 552), Reference class 3

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	Low and increasing	-6.89	1.08	< .001	0.00
Class 2	High and decreasing	-0.41	0.82	.618	0.67
Class 3 (ref)	High and relatively consistent	0.00			1.00
Class 4	Moderate and increasing	-2.97	0.47	< .001	0.05
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	Low and increasing	0.74	0.46	.109	2.09
Class 2	High and decreasing	-0.44	0.35	.203	0.64
Class 3 (ref)	High and relatively consistent	0.00			1.00
Class 4	Moderate and increasing	-0.14	0.25	.575	0.87

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 46

Diligence Four-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 552), Reference class 4

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	Low and increasing	-3.92	0.93	< .001	0.02
Class 2	High and decreasing	2.57	1.02	.012	13.01
Class 3	High and relatively consistent	2.97	0.47	< .001	19.58
Class 4 (ref)	Moderate and increasing	0.00			1.00
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	Low and increasing	0.88	0.43	.041	2.04
Class 2	High and decreasing	-0.38	0.38	.412	0.68
Class 3	High and relatively consistent	0.14	0.25	.575	1.15
Class 4 (ref)	Moderate and increasing	0.00			1.00

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 47

Future Mindedness Four-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 551), Reference class 1

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1 (ref)	Moderate and increasing	0.00			1.00
Class 2	High and relatively consistent	2.11	0.35	< .001	8.22
Class 3	High and decreasing	2.92	0.93	.002	18.60
Class 4	Low and increasing	-1.82	0.51	< .001	0.16
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1 (ref)	Moderate and increasing	0.00			1.00
Class 2	High and relatively consistent	0.93	0.32	.004	2.55
Class 3	High and decreasing	0.26	0.39	.508	1.30
Class 4	Low and increasing	0.02	0.18	.920	1.02

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 48

Future Mindedness Four-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 551), Reference class 2

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	Moderate and increasing	-2.11	0.35	< .001	0.12
Class 2 (ref)	High and relatively consistent	0.00			1.00
Class 3	High and decreasing	0.82	0.96	.393	2.26
Class 4	Low and increasing	-3.92	0.65	< .001	0.02
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	Moderate and increasing	-0.93	0.32	.004	0.39
Class 2 (ref)	High and relatively consistent	0.00			1.00
Class 3	High and decreasing	-0.68	0.44	.126	0.51
Class 4	Low and increasing	-0.92	0.34	.007	0.40

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 49

Future Mindedness Four-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 551), Reference class 3

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	Moderate and increasing	-2.92	0.93	.002	0.05
Class 2	High and relatively consistent	-0.82	0.96	.393	0.44
Class 3 (ref)	High and decreasing	0.00			1.00
Class 4	Low and increasing	-4.74	1.09	< .001	0.01
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	Moderate and increasing	-0.26	0.39	.508	0.77
Class 2	High and relatively consistent	0.68	0.44	.126	1.96
Class 3 (ref)	High and decreasing	0.00			1.00
Class 4	Low and increasing	-0.24	0.42	.563	0.79

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 50

Future Mindedness Four-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 551), Reference class 4

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	Moderate and increasing	1.82	0.51	< .001	6.15
Class 2	High and relatively consistent	3.92	0.65	< .001	50.50
Class 3	High and decreasing	4.74	1.09	< .001	114.21
Class 4 (ref)	Low and increasing	0.00			1.00
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	Moderate and increasing	-0.02	0.18	.920	0.98
Class 2	High and relatively consistent	0.92	0.34	.007	2.50
Class 3	High and decreasing	0.24	0.42	.563	1.27
Class 4 (ref)	Low and increasing	0.00			1.00

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 51

Purpose Six-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 549), Reference class 1

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1 (ref)	High and decreasing more steeply	0.00			1.00
Class 2	Low and relatively consistent	-1.40	0.42	.001	0.25
Class 3	Moderate and increasing	-0.68	0.34	.049	0.51
Class 4	Low and increasing	-1.94	0.71	.007	0.14
Class 5	High and decreasing	0.70	0.36	.053	2.01
Class 6	High and increasing	-0.22	0.51	.667	0.80
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1 (ref)	High and decreasing more steeply	0.00			1.00
Class 2	Low and relatively consistent	-0.52	0.34	.121	0.60
Class 3	Moderate and increasing	0.03	0.30	.914	1.03
Class 4	Low and increasing	0.94	0.47	.040	2.56
Class 5	High and decreasing	0.91	0.33	.006	2.49
Class 6	High and increasing	0.48	0.52	.350	1.62

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 52

Purpose Six-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 549), Reference class 2

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing more steeply	1.40	0.42	.001	4.04
Class 2 (ref)	Low and relatively consistent	0.00			1.00
Class 3	Moderate and increasing	0.72	0.31	.018	2.05
Class 4	Low and increasing	-0.55	0.65	.403	0.58
Class 5	High and decreasing	2.09	0.35	< .001	8.11
Class 6	High and increasing	1.18	0.37	.001	3.25
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing more steeply	0.52	0.34	.121	1.68
Class 2 (ref)	Low and relatively consistent	0.00			1.00
Class 3	Moderate and increasing	0.55	0.23	.017	1.74
Class 4	Low and increasing	1.46	0.42	< .001	4.31
Class 5	High and decreasing	1.43	0.28	< .001	4.18
Class 6	High and increasing	1.00	0.36	.005	2.73

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 53

Purpose Six-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 549), Reference class 3

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing more steeply	0.68	0.34	.049	1.97
Class 2	Low and relatively consistent	-0.72	0.31	.018	0.49
Class 3 (ref)	Moderate and increasing	0.00			1.00
Class 4	Low and increasing	-1.27	0.63	.046	0.28
Class 5	High and decreasing	1.38	0.24	< .001	3.96
Class 6	High and increasing	0.46	0.28	.099	1.59
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing more steeply	-0.03	0.30	.914	0.97
Class 2	Low and relatively consistent	-0.55	0.23	.017	0.58
Class 3 (ref)	Moderate and increasing	0.00			1.00
Class 4	Low and increasing	0.91	0.36	.012	2.48
Class 5	High and decreasing	0.88	0.20	< .001	2.41
Class 6	High and increasing	0.45	0.30	.126	1.57

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 54

Purpose Six-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 549), Reference class 4

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing more steeply	1.94	0.71	.007	6.99
Class 2	Low and relatively consistent	0.55	0.65	.403	1.73
Class 3	Moderate and increasing	1.27	0.63	.046	3.54
Class 4 (ref)	Low and increasing	0.00			1.00
Class 5	High and decreasing	2.64	0.69	< .001	14.01
Class 6	High and increasing	1.73	0.68	.011	5.62
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing more steeply	-0.94	0.47	.047	0.39
Class 2	Low and relatively consistent	-1.46	0.42	< .001	0.23
Class 3	Moderate and increasing	-0.91	0.36	.012	0.40
Class 4 (ref)	Low and increasing	0.00			1.00
Class 5	High and decreasing	-0.03	0.39	.938	0.97
Class 6	High and increasing	-0.46	0.42	.279	0.63

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 55

Purpose Six-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 549), Reference class 5

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing more steeply	-0.70	0.36	.053	0.50
Class 2	Low and relatively consistent	-2.09	0.35	< .001	0.12
Class 3	Moderate and increasing	-1.38	0.24	< .001	0.25
Class 4	Low and increasing	-2.64	0.69	< .001	0.07
Class 5 (ref)	High and decreasing	0.00			1.00
Class 6	High and increasing	-0.91	0.32	.005	0.40
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing more steeply	-0.91	0.33	.006	0.40
Class 2	Low and relatively consistent	-1.43	0.28	< .001	0.24
Class 3	Moderate and increasing	-0.88	0.20	< .001	0.42
Class 4	Low and increasing	0.03	0.39	.938	1.03
Class 5 (ref)	High and decreasing	0.00			1.00
Class 6	High and increasing	-0.43	0.34	.204	0.65

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 56

Purpose Six-class Latent Class Regression Results for the Associations between Intentional Self-regulation and Prosocial Socialization with Latent Class Membership (n = 549), Reference class 6

C regressed on *intentional self-regulation*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing more steeply	0.22	0.51	.667	1.24
Class 2	Low and relatively consistent	-1.18	0.37	.001	0.31
Class 3	Moderate and increasing	-0.46	0.28	.099	0.63
Class 4	Low and increasing	-1.73	0.68	.011	0.18
Class 5	High and decreasing	0.91	0.32	.005	2.49
Class 6 (ref)	High and increasing	0.00			1.00
C regressed on *prosocial socialization*		$\hat{\gamma}_{1k}$	*SE*	*p*-value	$\widehat{OR}$
Class 1	High and decreasing more steeply	-0.48	0.52	.350	0.62
Class 2	Low and relatively consistent	-1.00	0.36	.005	0.37
Class 3	Moderate and increasing	-0.45	0.30	.126	0.64
Class 4	Low and increasing	0.46	0.42	.279	1.58
Class 5	High and decreasing	0.43	0.34	.204	1.53
Class 6 (ref)	High and increasing	0.00			1.00

Note: $\hat{\gamma}_{1k}$ Coefficient of the predictor, *SE* Standard error, $\widehat{OR}$ Odds ratio

Table 57

Logistic Regression Analysis for the Associations between Intentional Self-regulation and Prosocial Socialization on Increasing Class Patterns (n = 552)

Variables	*B*	*SE*	*Wald*	*df*	*p*-value	$\widehat{OR}$	*95% CI*
Intentional self-regulation	-0.95	0.19	24.31	1.00	< .001	0.39	(0.26, 0.56)
Prosocial socialization	0.18	0.18	1.04	1.00	.307	1.20	(0.84, 1.70)
Constant	0.39	0.77	0.26	1.00	.609	1.48	

Note: B Coefficient of the predictor, *SE* Standard error of the coefficient of the predictor, *Wald* Wald test, *df* Degrees of freedom for the Wald test, *p-value p*-value of the Wald test, $\widehat{OR}$ Odds ratio, *95% CI* 95% Confidence interval of the Odds ratio

Table 58

Logistic Regression Analysis for the Associations between Intentional Self-regulation and Prosocial Socialization on Decreasing Class Patterns (n = 552)

Variables	*B*	*SE*	*Wald*	*df*	*p*-value	$\widehat{OR}$	*95% CI*
Intentional self-regulation	0.94	0.28	11.51	1.00	.001	2.56	(1.49, 4.40)
Prosocial socialization	-0.03	0.20	0.02	1.00	.901	0.98	(0.65, 1.46)
Constant	-6.34	1.16	30.06	1.00	< .001	0.02	

Note: B Coefficient of the predictor, *SE* Standard error of the coefficient of the predictor, *Wald* Wald test, *df* Degrees of freedom for the Wald test, *p-value* *p*-value of the Wald test, $\widehat{OR}$ Odds ratio, *95% CI* 95% Confidence interval of the Odds ratio.

Table 59

Logistic Regression Analysis for the Associations between Intentional Self-regulation and Prosocial Socialization on Consistently Mixed Class Patterns (n = 552)

Variables	*B*	*SE*	*Wald*	*df*	*p*-value	$\widehat{OR}$	*95% CI*
Intentional self-regulation	-1.35	0.17	66.89	1.00	< .001	0.26	(0.19, 0.36)
Prosocial socialization	-0.15	0.12	1.61	1.00	.205	0.86	(0.68, 1.09)
Constant	3.85	0.63	37.57	1.00	< .001	46.86	

Note: B Coefficient of the predictor, *SE* Standard error of the coefficient of the predictor, *Wald* Wald test, *df* Degrees of freedom for the Wald test, *p-value p*-value of the Wald test, $\widehat{OR}$ Odds ratio, *95% CI* 95% Confidence interval of the Odds ratio.

Table 60

Logistic Regression Analysis for the Associations between Intentional Self-regulation and Prosocial Socialization on Consistently High Class Patterns (n = 552)

Variables	*B*	*SE*	*Wald*	*df*	*p*-value	$\widehat{OR}$	*95% CI*
Intentional self-regulation	1.11	0.14	65.52	1.00	< .001	3.04	(2.32, 3.98)
Prosocial socialization	0.00	0.11	0.00	1.00	.986	1.00	(0.81, 1.23)
Constant	-3.48	0.54	42.14	1.00	< .001	0.03	

Note: B Coefficient of the predictor, *SE* Standard error of the coefficient of the predictor, *Wald* Wald test, *df* Degrees of freedom for the Wald test, *p-value p*-value of the Wald test, $\widehat{OR}$ Odds ratio, *95% CI* 95% Confidence interval of the Odds ratio.

Table 61

Findings

Analysis	*Research Question (RQ)*	*Results*
T-Test and Repeated Measures ANOVA	RQ1	No practical differences in honesty between in-school or online samples or longitudinally
Confirmatory Factor Analyses	RQ1	Humility, diligence, future mindedness, and purpose confirmed structurally
Measurement Invariance – Between-group and Longitudinal	RQ1	Character attributes confirmed to hold between groups and longitudinally
Latent Growth Curve Models	RQ1	Well-fitting non-mixture growth models
Growth Mixture Modeling	RQ1	Six-class LCGA models for honesty, humility, and purpose Four-class LCGA models for diligence and future mindedness
Correlations	RQ2	All class-level predicted character attributes significantly correlated with one another within and across time points
Multinomial Logistic Regressions by attribute	RQ3	For all character attribute trajectories, higher intentional self-regulation predicted high start points for each attribute but did not appear to have a sustained positive effect. Higher prosocial socialization predicted class membership for purpose without a clear pattern.
Logistic regressions for class patterns	RQ3	Intentional self-regulation was associated with higher start points. Prosocial socialization was not associated with any patterns.

Note: *ANOVA* Analysis of variance

Figures

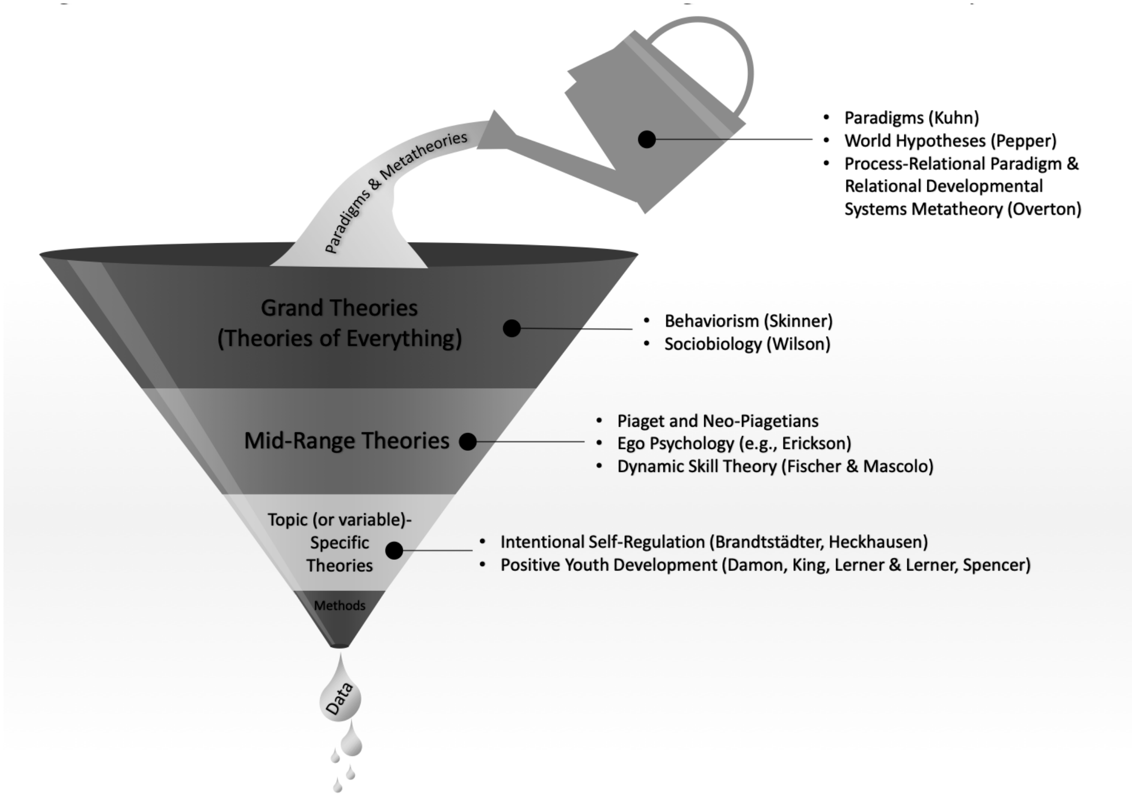


Figure 1. A Funnel Model of Levels of Theoretical Integration in Human Development (J. Lerner, personal communication, February 22, 2017)

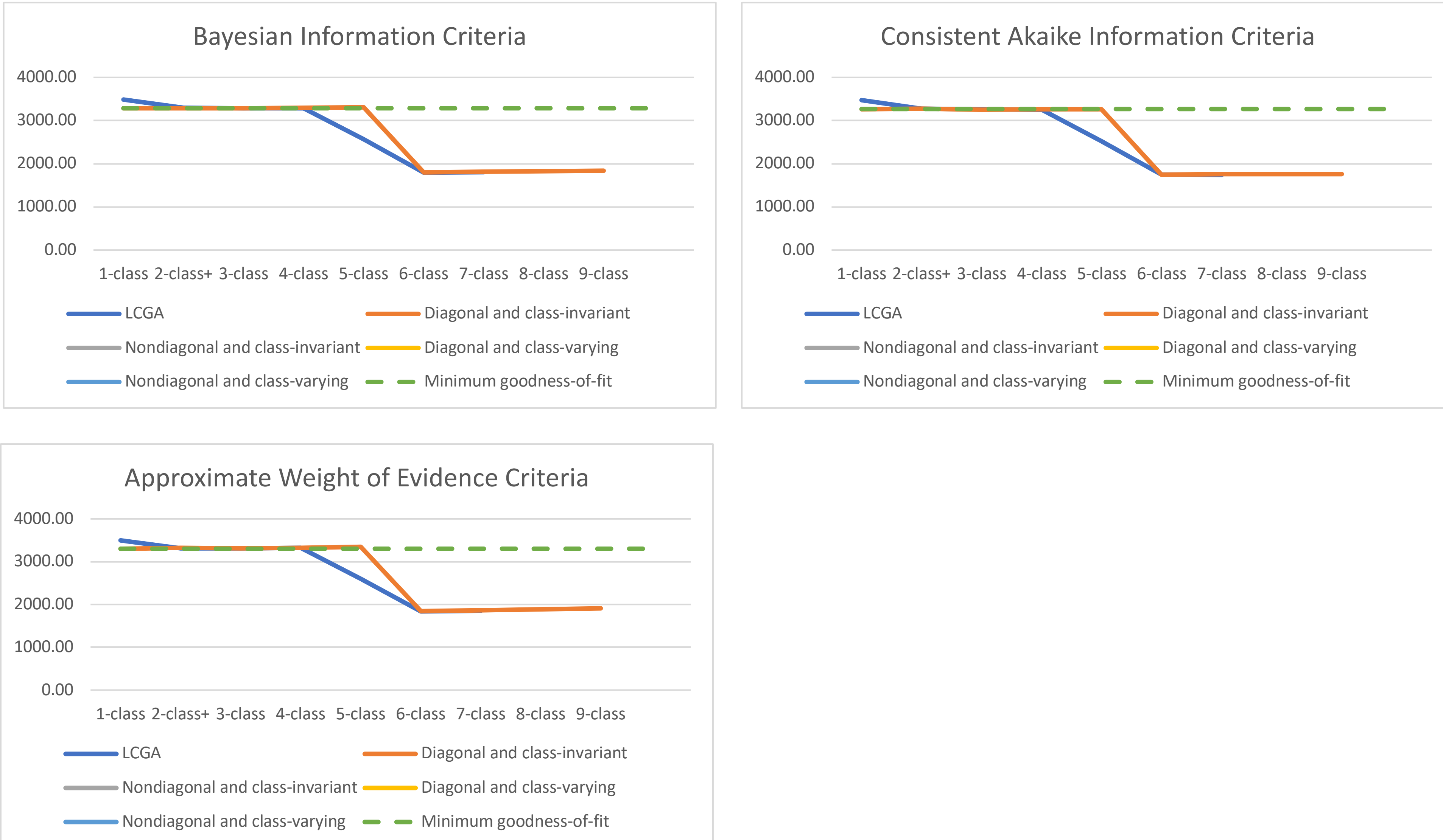
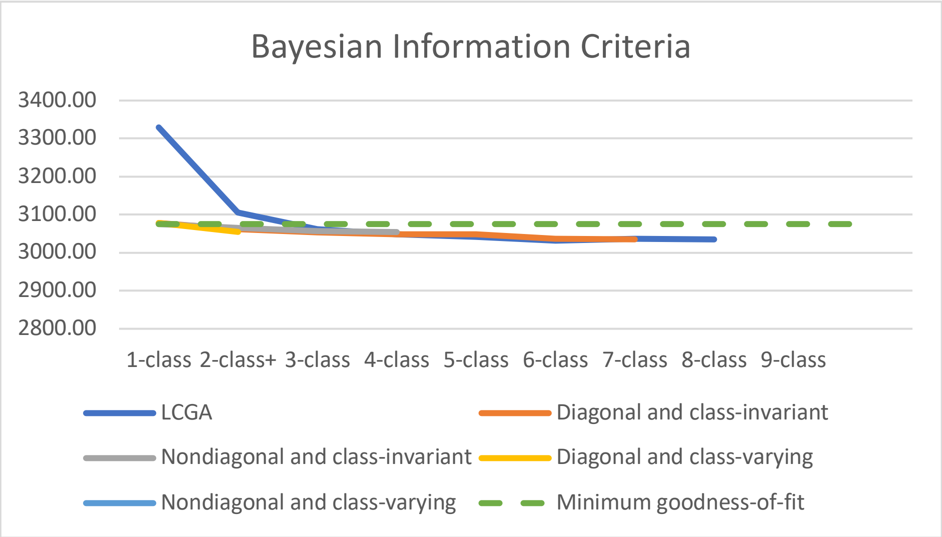
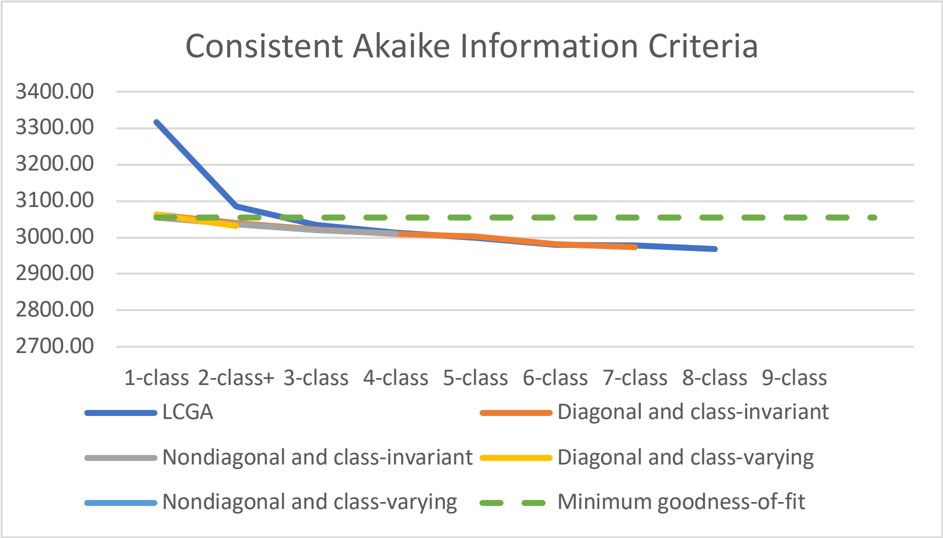


Figure 2. *Honesty Elbow Plots.*
Note: LCGA Latent class growth analysis





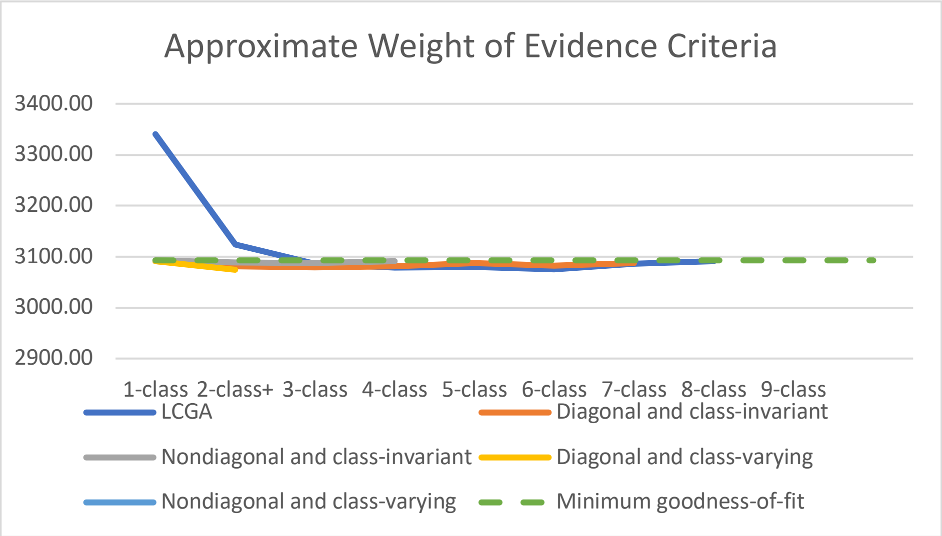
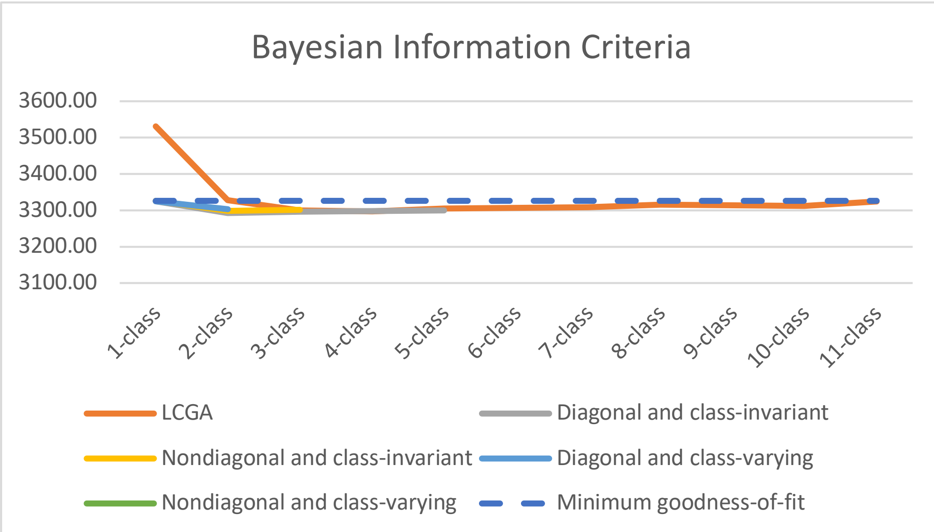
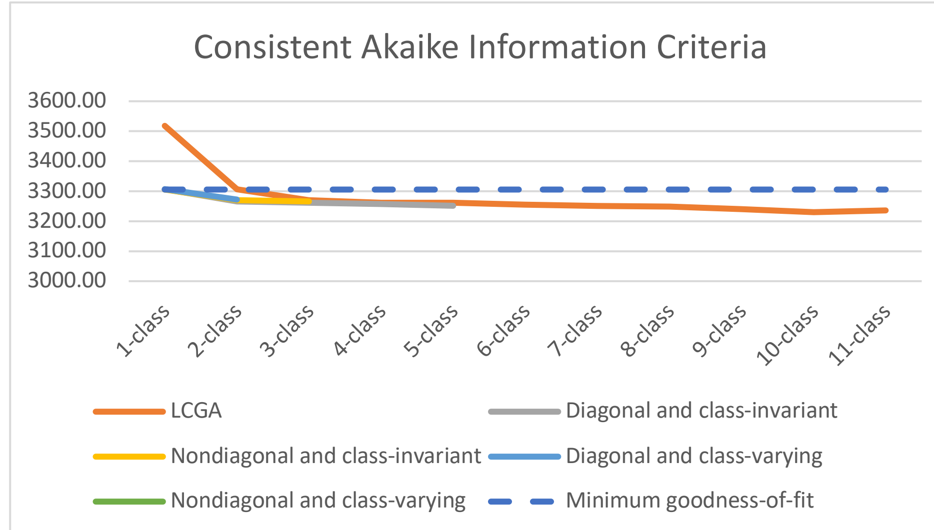


Figure 3. *Humility Elbow Plots.*
Note: LCGA Latent class growth analysis





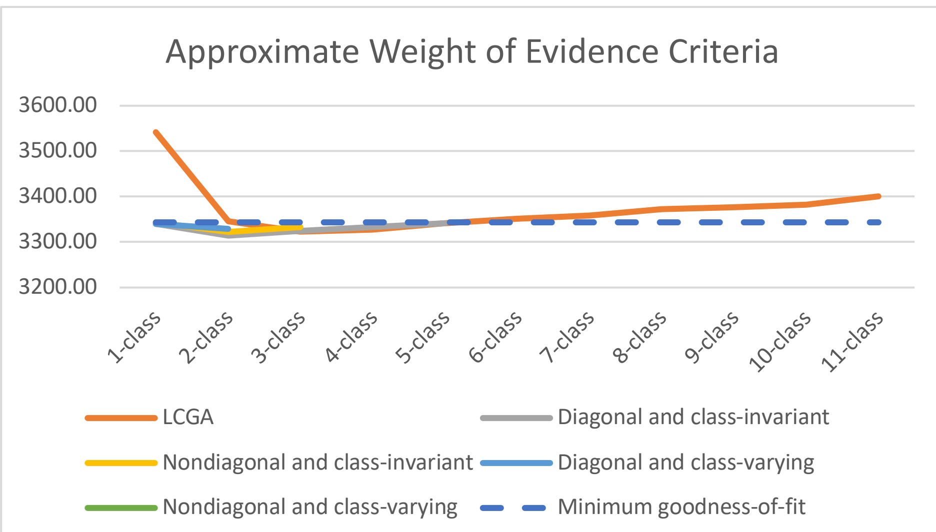


Figure 4. *Diligence Elbow Plots.*
Note: LCGA Latent class growth analysis

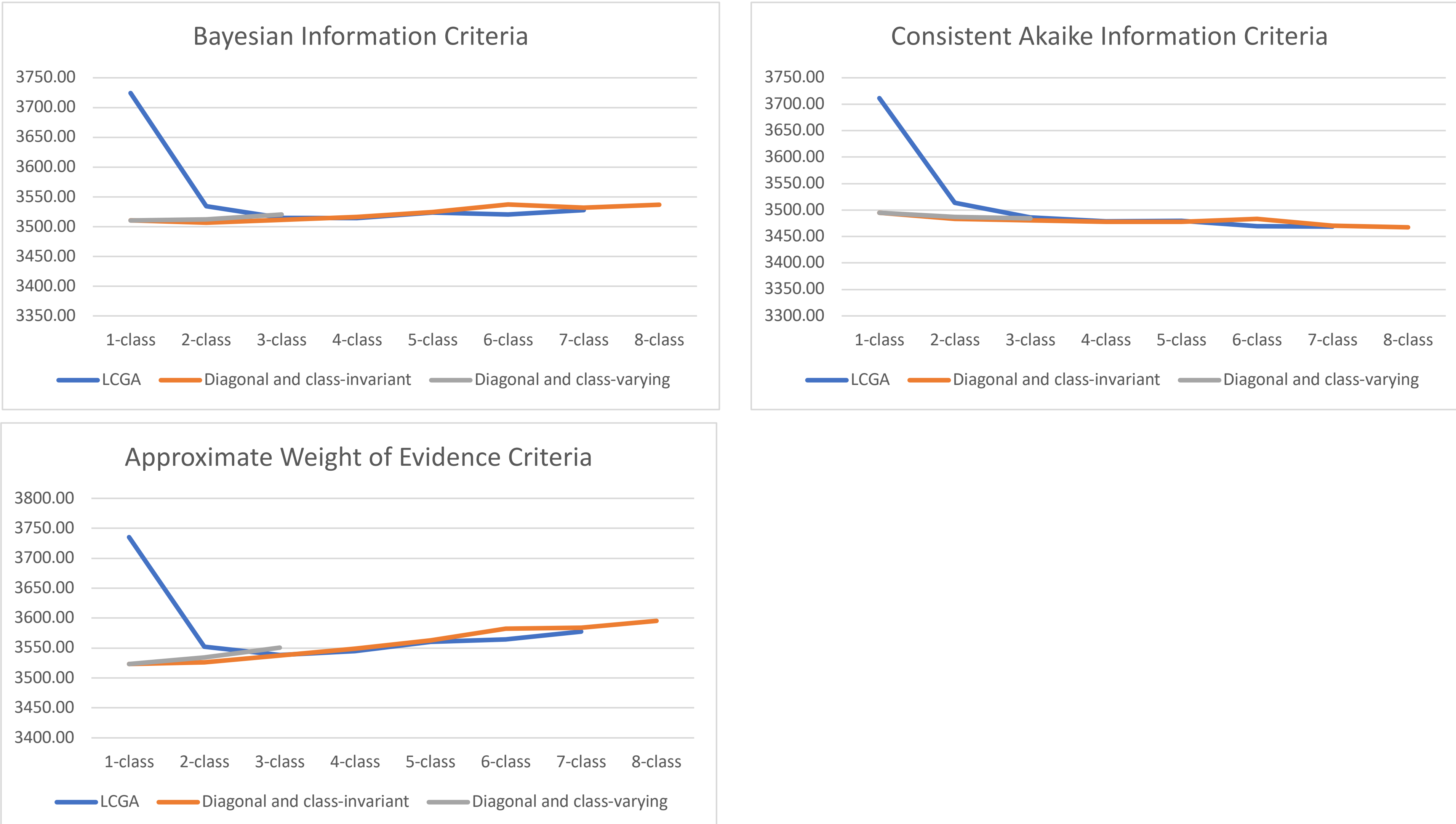


Figure 5. *Future mindedness Elbow Plots.*
Note: LCGA Latent class growth analysis*,* No minimum goodness-of-fit available.

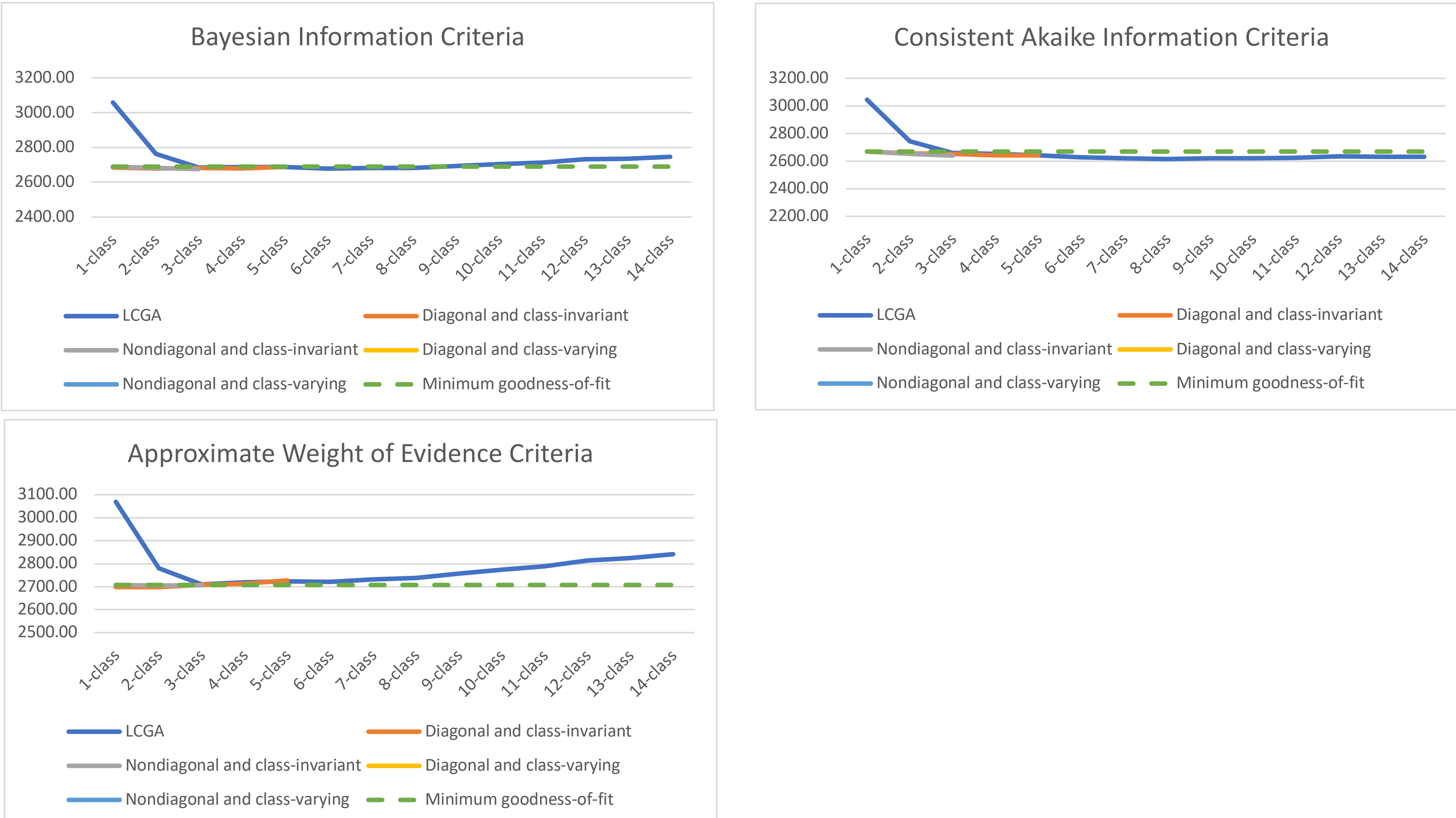


Figure 6. *Purpose Elbow Plots*
Note: LCGA Latent class growth analysis,

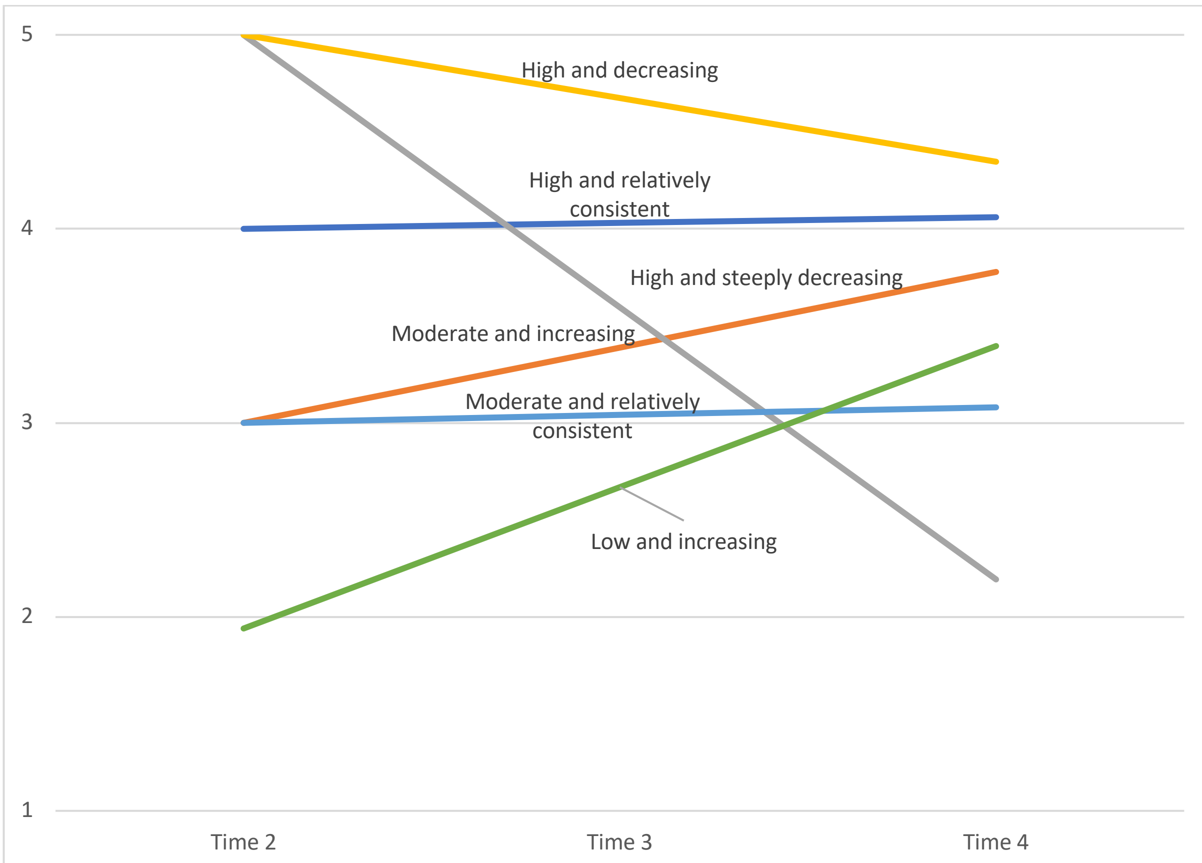


Figure 7. *Honesty Six-class Latent Class Growth Analysis Plot.*

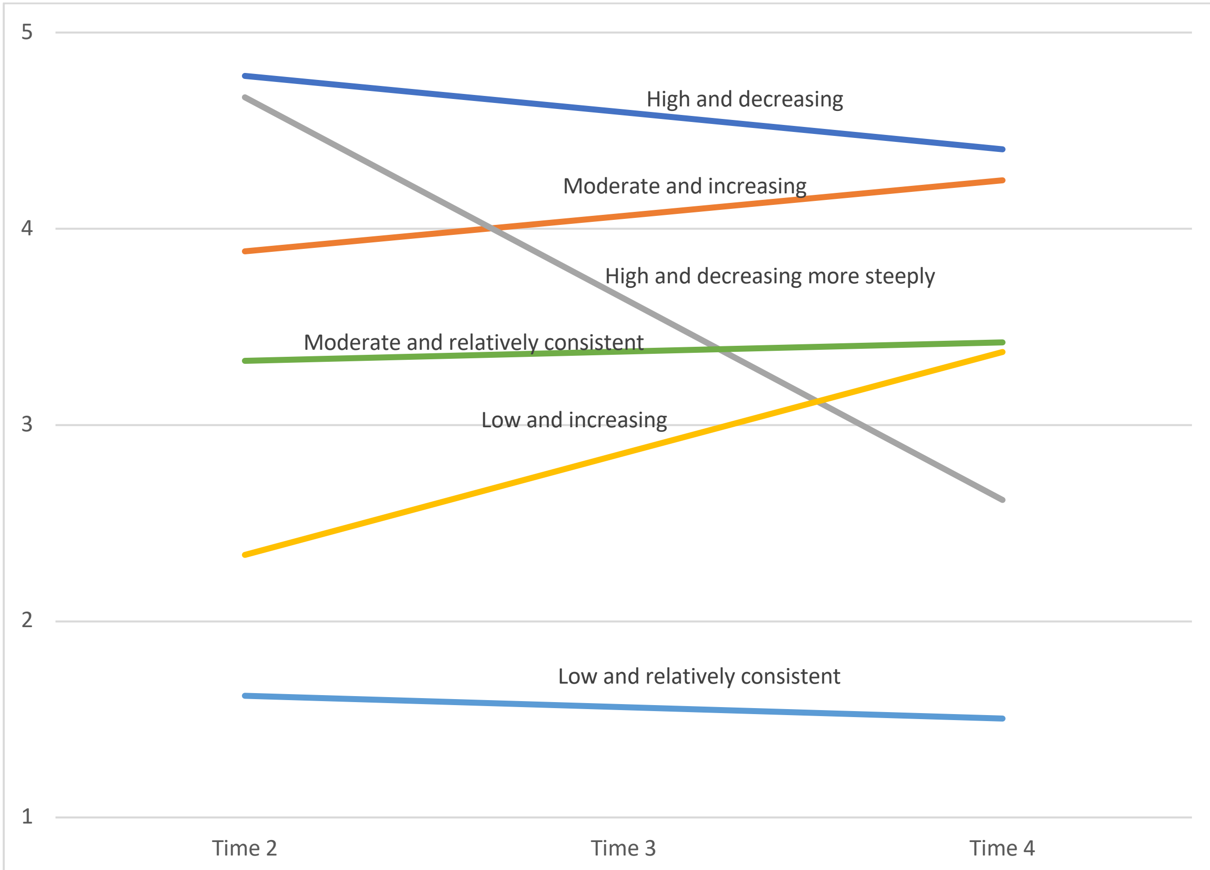


Figure 8. *Humility Six-class Latent Class Growth Analysis Plot.*

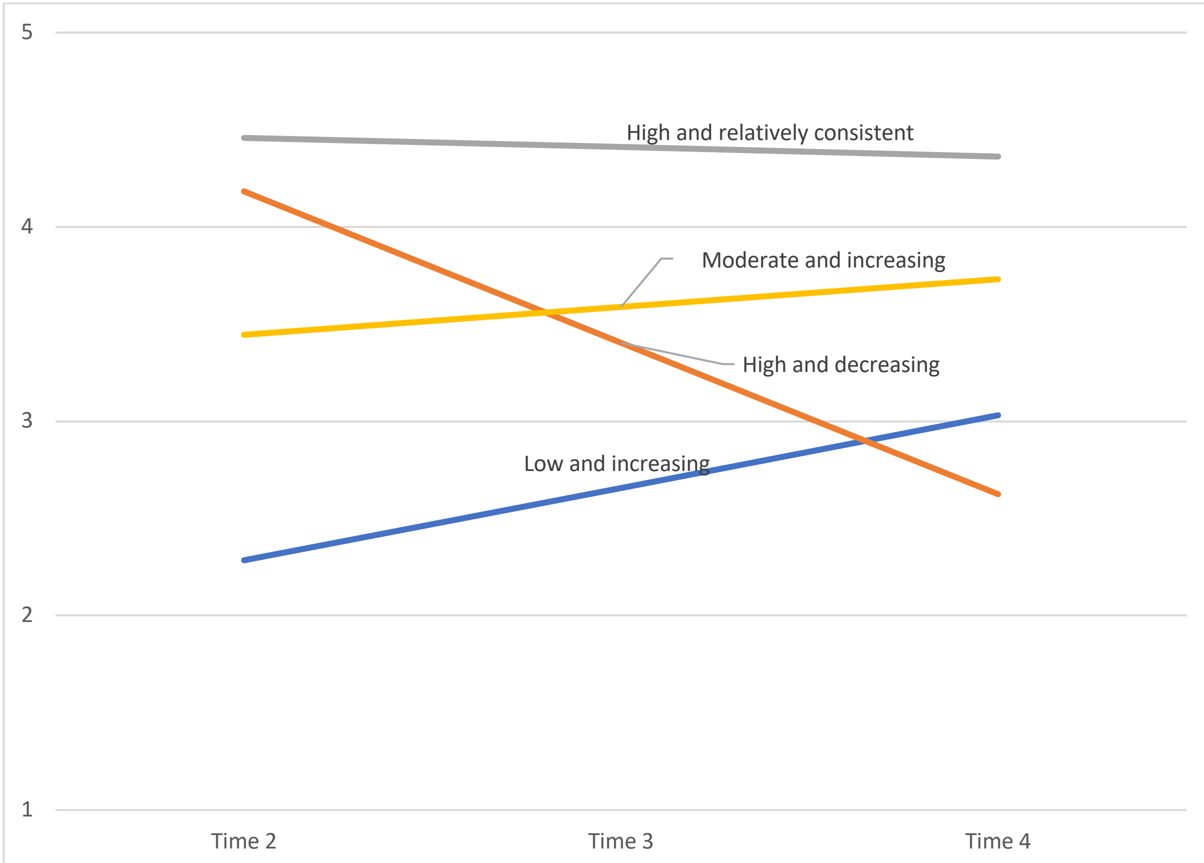


Figure 9. *Diligence Four-class Latent Class Growth Analysis Plot.*

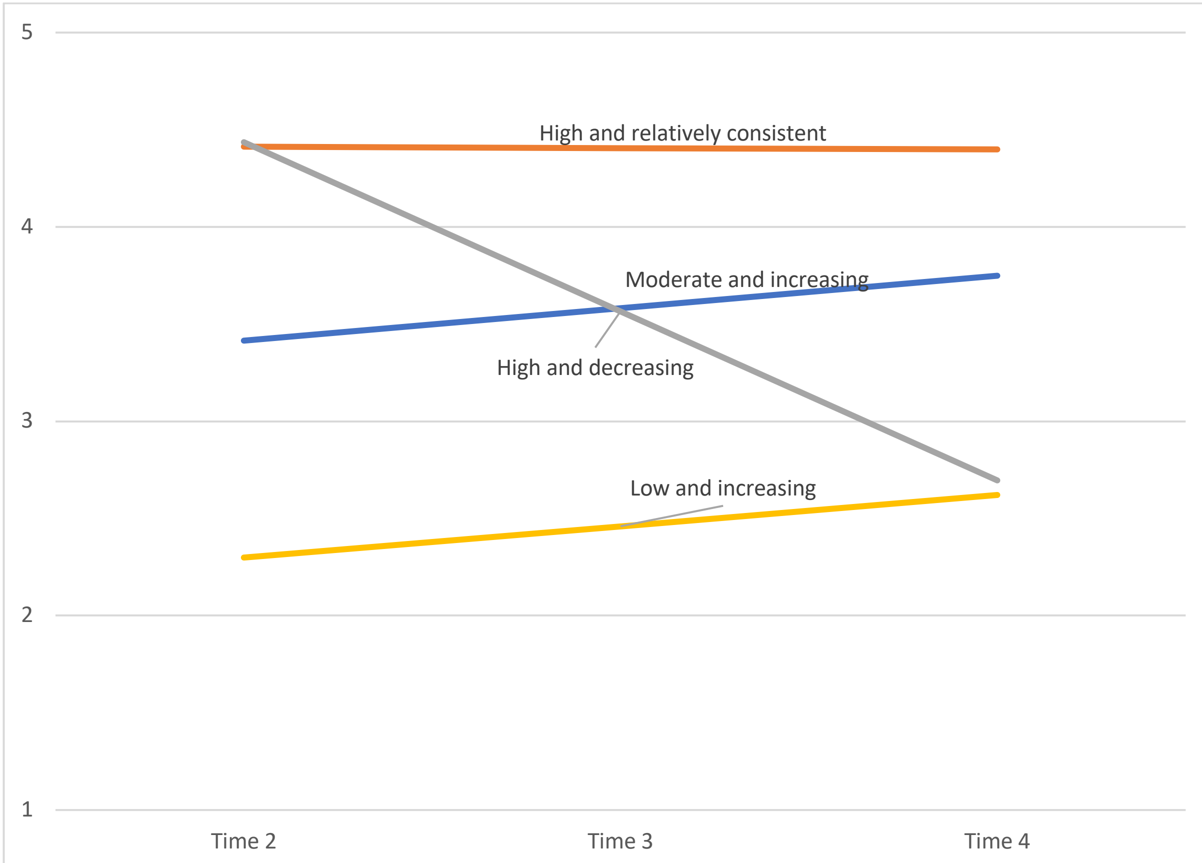


Figure 10. *Future Mindedness Four-class Latent Class Growth Analysis Plot.*

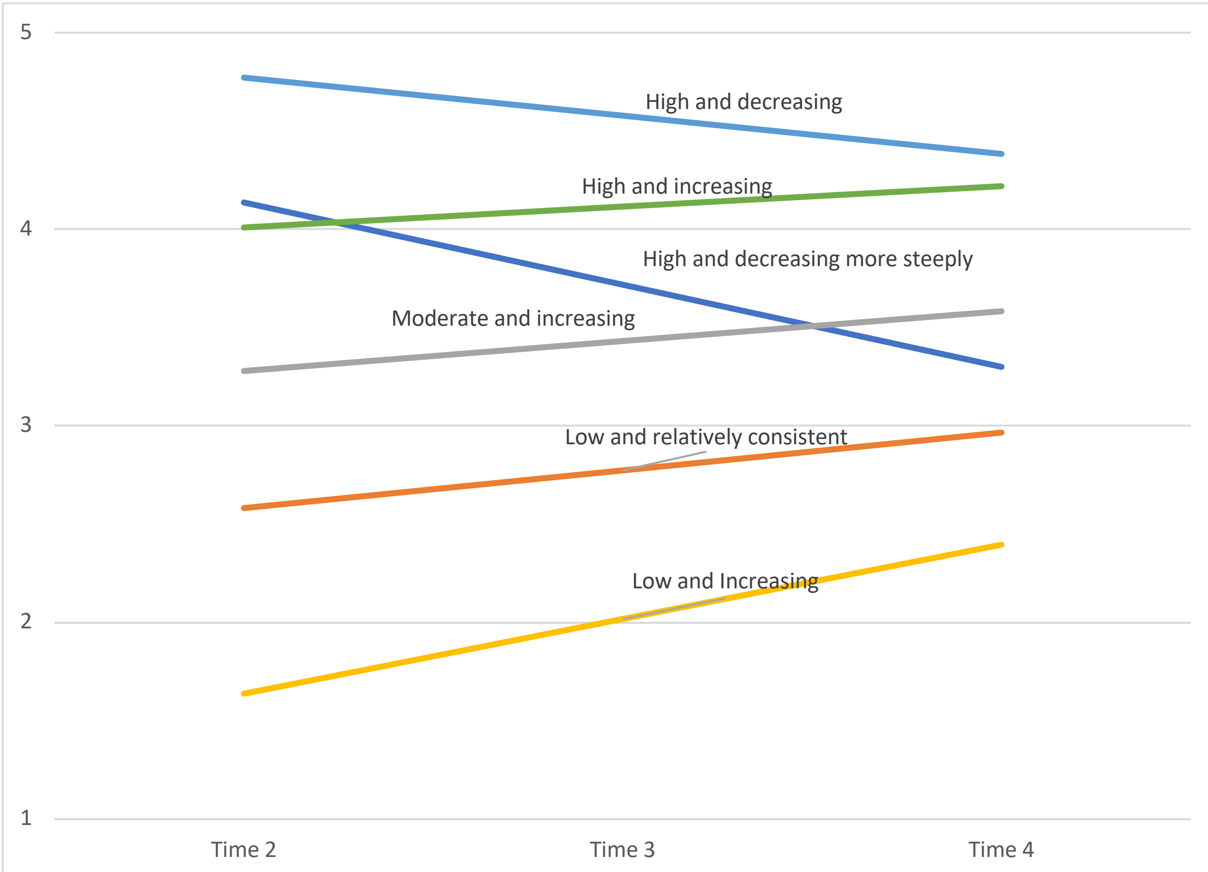


Figure 11. *Purpose Six-class Latent Class Growth Analysis Plot.*